Analysts' Reputational Concerns, Self-censoring and the International Dispersion Effect[a]

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Abstract

Stocks with higher forecast dispersion earn lower future returns and have a greater upward bias in the mean reported earnings forecast in the international markets. Both phenomena are stronger in countries with more transparent information environments, more developed stock markets, stronger investor protection, greater capital openness, and more intense usage of analysts' earnings forecasts. Using the 1997−98 Asian financial crisis as a natural experiment, we find that both phenomena become weaker post crisis in Malaysia, which imposed capital controls, relative to Thailand and South Korea, which opened up their financial markets to foreigners. These results suggest that analysts in countries with greater demand for their forecasts and hence greater concerns for reputations are more likely to self-censor their low forecasts, which leads to a stronger dispersion-bias relation and a stronger dispersion effect.

Keywords: analysts' incentives; analysts' reputational concerns; self-censoring; the dispersion effect; international markets

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1. Introduction

Diether, Malloy, and Scherbina (henceforth DMS) (2002) document the dispersion effect: a negative cross-sectional relation between the dispersion in analysts' earnings forecasts and future returns of U.S. stocks. This is viewed as anomalous because dispersion is often considered as a proxy for risk and we would normally expect bearing larger risk to be compensated by higher future expected return. This study contains two main new results about the dispersion effect. First, the dispersion effect is an international phenomenon. Second, and more importantly, the dependence of the dispersion effect on country characteristics provides strong evidence that the dispersion effect is due to analysts' incentives, not to other proposed mechanisms. We consider various country characteristics including information environment, stock market development and investor protection. We obtain especially strong evidence from a series of difference-in-differences results from the capital control changes in Malaysia, Thailand and South Korea during the 1997−98 Asian financial crisis.

The literature offers three explanations for the dispersion effect. The first explanation by DMS (2002), based on Miller's (1977) theory, posits that forecast dispersion is a proxy for different opinions among investors (the difference-in-opinion explanation). Due to short-sale constraints, stock prices reflect only optimistic views as investors with pessimistic views cannot trade; this introduces an optimistic bias into the prices of stocks about which investors hold divergent opinions (i.e., high-dispersion stocks). The second explanation, also by DMS (2002), is that analysts' incentive structure encourages them to self-censor their unfavorable earnings forecasts (the analyst-incentive explanation). The more spread out the underlying earnings forecasts, the more pessimistic are the self-censored forecasts, and the greater the upward bias in the mean reported forecast. This leads to a positive relation between the upward bias in the mean reported forecast and the dispersion of analysts' reported forecasts (henceforth the dispersion-bias relation). If investors do not properly adjust for this bias, they will overvalue stocks with higher forecast dispersion, which results in a negative relation between forecast dispersion and future stock returns. The third explanation by Johnson (2004) argues that forecast dispersion is a proxy for idiosyncratic parameter risk. In the presence of leverage, expected returns decrease with idiosyncratic parameter risk, as equity is a call option on a firm's assets and the option value increases with idiosyncratic asset risk (the parameter-risk explanation).[1]

[1] Two other papers are relevant to our discussion of the dispersion effect. Sadka and Scherbina (2007) demonstrate that firms with high forecast dispersion tend to have high trading costs, which explains the persistence of the dispersion effect but does not explain why the dispersion effect occurs in the first place. Avramov et al. (2009) argue that forecast dispersion reflects uncertainty about current earnings, which is one of the components of asset valuation. On the other hand, default risk captures the uncertainty of more ingredients used in asset valuation, including current earnings, growth rates, and the cost of equity. Hence, the dispersion effect is a manifestation of the puzzling negative relation between default risk and future stock return.

We first investigate whether the dispersion effect exists in the international markets. Our answer to this question is affirmative. We find that the average monthly return (both raw and risk-adjusted returns) on a portfolio that buys stocks in the lowest dispersion quintile and sells stocks in the highest dispersion quintile is positive and significantly different from zero (at a significance level of 0.05) in 19 out 23 international markets. Pooling firms in all international markets together, we find that in both the international markets and the U.S. market, forecast dispersion has a stronger (i.e., more statistically significant) return-predictive ability than size, book-to-market, and past stock return during our sample period from January 1990 to December 2013.

We then investigate how the dispersion effect varies across countries. We find that the dispersion effect is stronger in countries with more transparent information environments, more developed stock markets, greater capital openness, stronger investor protection, and more intense usage of analysts' earnings forecasts. These results are consistent with the prediction from a model which considers cross-country variation in analysts' reputational concerns. Similar to Scherbina (2005), this model extends DMS's (2002) and Scherbina's (2008) analyses on self-censoring to consider analysts' choice between self-censoring and adding an optimistic bias to their true forecasts and the resulting relation between the bias and the dispersion in analysts' reported forecasts. The central idea of the model is as follows. The firm manager will severely penalize analysts who report forecasts below the manager's threshold forecast, but will not reward those who report optimistic forecasts above the threshold. Thus, when an analyst's true forecast falls below the threshold forecast, she either self-censors her true forecast *or* adds an optimistic bias to her true forecast to report the threshold forecast. However, adding an optimistic bias creates forecast error and damages her reputation. Therefore, in environments where reputation is important, she is more likely to choose self-censoring to preserve her reputation. Self-censoring increases upward bias in the mean reported forecast relative to the true mean forecast more than adding an optimistic bias to report the threshold forecast does. Furthermore, the bias in the mean reported forecast is larger the more dispersed the distribution of analysts' *underlying* forecasts (i.e., a larger σ) and consequently the more dispersed the distribution of analysts' *reported* forecasts (i.e., a larger σ_{rep}),[2] indicating a positive dispersion-bias relation. Therefore, in countries where analysts care more about their reputations, more analysts will choose self-censoring over adding an optimistic bias, leading to a stronger positive dispersion-bias relation and a stronger dispersion effect. Since analysts' reputational concerns rise with investor demand for analyst forecasts (Barniv et al. 2005), the dispersion effect should be stronger in countries where investor demand for analyst forecasts is higher.

[2]As shown in Scherbina (2005), the dispersion in analysts' reported forecasts (i.e., forecast dispersion) increases with the dispersion in analysts' underlying forecasts.

Note that the positive dispersion-bias relation is unique to the analyst-incentive explanation. We find that 1) the positive dispersion-bias relation documented by DMS (2002) in the U.S. also exists in the international markets, and 2) this positive dispersion-bias relation is stronger in countries where investor demand for analyst forecasts is higher. These findings provide further support to the analyst-incentive explanation.

To address the concern that the cross-country findings are driven by unobservable variables, we conduct difference-in-differences tests using the 1997-98 Asian financial crisis as a natural experiment. In response to the crisis, South Korea and Thailand asked for help from IMF, which required opening their financial markets to foreigners, while Malaysia imposed sweeping capital controls (Dornbusch 2001, Kaplan and Rodrik 2001). Consequently, we expect the demand for analyst forecasts and hence analysts' reputational concerns in Malaysia to become relatively weaker as its market becomes less open after the crisis. The results from the difference-in-differences tests reveal that analysts' reputational concerns, and hence the dispersion effect and the positive dispersion-bias relation in Malaysia became weaker after the crisis relative to South Korea and Thailand, consistent with the analyst-incentive explanation.

In contrast, our evidence does not support the difference-in-opinion explanation or the parameter-risk explanation. A commonality in these two explanations is that *analysts*' disagreement about a firm's *earnings* is used as a proxy for *investors*' disagreement about a firm's *value*.[3] This proxying process requires two mappings: one from "analysts" to "investors" and the other from "earnings" to "firm value". Because (1) *firm value* is more difficult to forecast than *earnings* and (2) *investors* are less experienced than *analysts*, a given level of forecast dispersion should translate into a higher level of disagreement on firm value among investors, especially in a more uncertain environment where information is less precise and less available. Thus, both explanations suggest that the dispersion effect should be stronger in countries with more uncertain information environments. However, our finding shows the opposite.[4]

We make two contributions to the literature. First, using international data, we provide an out-of sample test for DMS's (2002) finding. Second, our cross-country analyses and difference-in-differences tests offer new evidence that is most consistent with the analyst-incentive explanation for the dispersion effect.[5] This is especially important, as the current literature seems to have largely ignored this

[3] The parameter-risk explanation in Johnson (2004) rests on the foundation that uncertainty (i.e., parameter risk) and investors' disagreement on firm value are closely linked.

[4] Such mappings are not required in the analyst-incentive explanation.

[5] In untabulated analyses, we examine the impact of firm leverage on the dispersion effect in international markets. According to Johnson (2004), one prediction from the parameter-risk explanation is that the dispersion effect should grow stronger as leverage becomes higher. The empirical results of testing this prediction in the U.S. market are mixed. Johnson (2004) finds results consistent with this prediction. On the other hand, both Sadka and Scherbina (2007) and Avramov et al. (2009) find that leverage is not relevant to the dispersion effect when they use a different U.S. sample from that in Johnson (2004). We do not find support for this prediction in the international markets. We also examine the impact of short

explanation; most of the studies mentioning the dispersion effect refer only to the difference-in-opinion explanation or to a less extent, the parameter-risk explanation.

2. Sample and data

The data on analysts' earnings forecasts are obtained from the Institutional Brokers Estimate System (I/B/E/S). Dispersion in analysts' earnings forecasts (*DISP*) is calculated as the ratio of the standard deviation of analysts' current fiscal-year annual earnings-per-share forecasts (i.e., forecasts of forthcoming earnings-per-share) to the absolute value of the mean forecast,[6] as reported in the I/B/E/S Summary History file. In the standard issue of I/B/E/S data, analyst forecasts are adjusted historically for stock splits, which renders these data unsuitable for the analysis of forecast dispersion (DMS 2002). Accordingly, we follow DMS (2002) in estimating forecast dispersion on the basis of analyst forecasts unadjusted for stock splits.

We retrieve the monthly return indexes of individual stocks (U.S. dollar denominated) from Thomson Datastream to calculate the monthly returns of non-U.S. stocks. We include both domestic and foreign stocks that are listed on the major stock exchange(s) in each country, as in Chui et al. (2010). We also include only primary listings. Following McLean et al. (2009), we trim the returns of non-U.S. stocks at the top and bottom 1% within each country, as many of these extreme returns are likely to be the result of coding error. The returns of U.S. stocks, which are not trimmed, are taken from the Center for Research in Security Prices (CRSP). We also trim the forecast error, calculated as the absolute value of the ratio of the difference between monthly mean reported forecast and actual earnings-per-share to the latter, at the top 99% within each country,[7] because these forecasts are likely to be the results of data errors. We obtain the market value of equity (*MV*) and book-to-market ratio (*BM*) for non-U.S. stocks and U.S. stocks from Datastream and COMPUSTAT, respectively. We calculate return momentum (*MOM*) for each stock as its buy-and-hold return over the previous six months. We require all observations to have non-missing *DISP* and *MV*. As explained later, we create dummy variables for observations with missing *BM* and *MOM*. To eliminate the effects of outliers, we follow McLean et al. (2009) to winsorize the above characteristics (i.e., *DISP, MV*, *BM* and *MOM*) within each country at the top and bottom 1%. Furthermore, for each month we limit our sample to countries with at least 100 observations. This is

sale constraints on the dispersion effect in international markets. Using the legality of short selling as a proxy for the short sale constraint, we find that there is *no* significant difference in the dispersion effect between countries where short selling is banned and those where short selling is permitted. The information on whether short selling is allowed in a country is from Bris et al. (2007). However, this finding should be interpreted with caution because there are only a few countries in our sample where short selling is not allowed, which results in a very small variation of short sale constraints in our international sample.

[6] We regard *DISP* as missing if the mean forecast is 0. Results are similar if we assign the highest value of *DISP* in a country to observations with mean forecast equal to 0.

[7] The lower bound of forecast error is 0.

because we would like each dispersion quintile portfolio to have at least 20 stocks each month so that a portfolio return is less likely to be influenced by the extreme returns of some individual stocks in the portfolio. Finally, we exclude countries with a return history of fewer than 60 months over our sample period, which runs from February 1990 to December 2013. The choice of 60 is a trade-off result between two factors: a long return history for each country and a large number of countries in our sample.

Our final sample, which is described in Table 1, comprises 1,241,339 stock-month observations from 23 non-U.S. countries and 902,373 stock-month observations from the U.S.[8] The U.S. accounts for 42.1% of the total observations, by far the largest proportion, followed by Japan and the U.K., which account for 10.2% and 8.6% of the total, respectively. The number of months over the sample period is different across countries due to data availability. In columns 3 – 6 of Table 1, we show for each country the time-series average of monthly number of stocks, the percentage of I/B/E/S stocks covered by at least two analysts, and the percentage of Datastream stocks covered by I/B/E/S. In the last five columns of Table 1, we report for each country the time-series average of the median values of the following stock characteristics: number of analysts covering the stock (*COV*), natural logarithm of market value of equity (*LOGMV*), natural logarithm of book-to-market ratio (*LOGBM*), return momentum (*MOM*), and forecast dispersion (*DISP*).

3. The dispersion effect in the international markets

In this section, we investigate whether forecast dispersion can predict the cross-section of stock returns in the international markets using both the portfolio strategy and the regression method.

3.1 Portfolio strategy

At the end of each month, we assign all of the stocks within each country to five quintiles (D1 to D5) based on forecast dispersion. D1 includes stocks with the lowest forecast dispersion, while D5 includes stocks with the highest forecast dispersion. After being assigned to portfolios, stocks are held for one month. D1 − D5 is the hedge portfolio that holds a long position in stocks within D1 and a short position in stocks within D5 (henceforth called the dispersion portfolio). The monthly return of each portfolio is calculated as the equal-weighted average of the returns of all of its stocks.[9]

Panel A of Table 2 reports the results of the portfolio strategy for each of the 23 non-U.S. countries. With the exception of China and Turkey, the average monthly returns on the dispersion portfolio (D1 − D5) are positive in all of the non-U.S. countries; that is, in 21 of these countries. Under the null hypothesis that the dispersion effect is a random event, the probability of observing a positive (negative) average monthly return on D1 − D5 in any country is 0.5. Assuming that the sign of the average monthly

[8] Please see the online appendix for the detailed sample selection procedures for non-U.S. stocks.
[9] We repeat our analyses by calculating value-weighted returns and we find similar results (available on request).

return on D1 − D5 in any country follows a *Binomial* distribution ($\chi \sim B$ (N=23, P=0.5)),[10] the probability of observing 21 positive signs among the 23 non-U.S. countries is 0.000. This result thus strongly rejects the null hypothesis, which suggests that the dispersion effect is a prevalent anomaly around the world. Furthermore, the magnitude of the average monthly return on the dispersion portfolio is significantly positive (at a significance level of 0.05) in 19 of the 23 non-U.S. countries. The results based on the risk-adjusted returns (i.e., FF3 alpha) show a similar pattern. FF3 alpha is the intercept from regressing the monthly returns of the dispersion portfolio (D1 − D5) onto the local Fama-French three factors in each country. We follow Ang et al. (2009) to calculate the local Fama-French three factors. The local market factor is the value-weighted excess return of the stocks in each of our non-U.S. countries over the one-month U.S. T-bill rate. The local size (book-to-market) factor is the value-weighted return of the portfolio which consists of one third of the stocks with the smallest size (the highest book-to-market) in each non-U.S. country minus the return of the portfolio consisting of one third of the stocks at the opposite end.

Panel B of Table 2 reports the results of the aggregate portfolio strategy in the non-U.S. countries. Following Chui et al. (2010), we create two types of non-U.S. aggregate dispersion portfolios. We refer to the first type as the country-average dispersion portfolio, and the second as the country-composite dispersion portfolio. For each month, the country-average dispersion portfolio equally weights each country-specific dispersion portfolio, as described in Panel A. The composite dispersion portfolio is weighted more toward countries with more stocks. Specifically, at the end of each month, all stocks in each of the non-U.S. countries are ranked in ascending order based on forecast dispersion. Stocks in the top quintile of forecast dispersion in each country are assigned to the "D5" composite portfolio, and the bottom quintile stocks are assigned to the "D1" composite portfolio. The results in Panel B show that the time series average of the monthly return on the country-average dispersion portfolio is 0.77, and its *t*-statistic is 6.12. The time series average of the monthly return on the country-composite dispersion portfolio is 0.73, and its *t*-statistic is 5.54. The *t*-statistics are calculated based on Newey-West (1994) heteroskedasticity and autocorrelation consistent standard errors.[11]

The results based on the risk-adjusted returns show a similar pattern as well. The FF3 alpha of the country-average portfolio is the intercept from regressing the country-average dispersion portfolio (D1 − D5) onto the country-average Fama-French three factors, which are the value-weighted average of each of the three local factors among our non-U.S. countries. The FF3 alpha of the country-composite portfolio is the intercept from regressing the country-composite dispersion portfolio (D1 − D5) onto the country-composite Fama-French three factors. The construction of the country-composite Fama-French three factors is similar to that of the country-average factors, except that greater weights are put on countries

[10] The binomially distributed random variable χ is the sign on the dispersion effect in a financial market.

[11] As suggested by Newey and West (1994), we select the lag length (L) that equals the integer portion of $12(T/100)^{2/9}$, where T is the number of observations.

with more stocks as in the construction of the country-composite dispersion portfolios. The FF3 alpha of the country-average dispersion portfolio is 1.05, and its *t*-statistic is 6.17. The FF3 alpha of the country-composite dispersion portfolio is 1.29, and its *t*-statistic is 8.21.

3.2 Regression analysis

We run the following Fama-MacBeth (1973) cross-sectional regressions on both non-U.S. and U.S. stocks, respectively:

$$RET_{i,t+1} = \beta_0 + \beta_1 DISP_{i,t} + \beta_2 LOGMV_{i,t} + \beta_3 LOGBM_{i,t} + \beta_4 BMDUM_{i,t} + \beta_5 MOM_{i,t} + \beta_6 MOMDUM_{i,t} + \varepsilon_{i,t+1}. \quad (1)$$

$RET_{i,t+1}$ is the return of stock i in month $t+1$. Following Pontiff and Woodgate (2008), we create a book-to-market dummy variable (*BMDUM*). If the book value of equity is either missing or negative, then we assign both *LOGBM* and *BMDUM* values of zero. Otherwise, *BMDUM* is set to one. Similarly, we create a momentum dummy variable (*MOMDUM*). If the buy-and-hold return over the previous six months is unavailable, then we assign both *MOM* and *MOMDUM* values of zero. Otherwise, *MOMDUM* is set to one. The use of *BMDUM* and *MOMDUM* allows us to include stocks with missing *LOGBM* or *MOM* in the regression without influencing the inference of the *LOGBM* and *MOM* slope coefficients (Pontiff and Woodgate 2008). Following Chui et al. (2010), we use Newey-West (1994) heteroskedasticity and autocorrelation consistent standard errors to compute the *t*-statistics on the Fama-MacBeth coefficients.

The results of the regression analyses are reported in Panel C of Table 2. The coefficients on *DISP* are negative and significant in the regressions carried out on non-U.S. stocks, which suggests that forecast dispersion has a significant and persistent ability to predict cross-sectional returns, both across countries (without country dummies) and within a country (with country dummies). In addition, the results show that among both non-U.S. and U.S. stocks, the *t*-statistic of the coefficient on *DISP* is greater than that of *LOGMV*, *LOGBM*, or *MOM.* These results suggest that the dispersion effect is more significant than the size, value and momentum effects during our sample period.

4. Determinants of cross-country differences in the dispersion effect

In section 3, we observed a wide variation in the strength of the dispersion effect across countries. In this section, we investigate how this effect is associated with country characteristics. As will become clearer later, this investigation can help shed light on the alternative explanations for the dispersion effect mentioned in the introduction.

Since we have a long sample period which ranges from 1990 to 2013, some country characteristics are likely to change substantially over time. Hence, we use the most recent available information to construct a country characteristic which varies by year. In order to allow for comparison across years, each year, we transform the values of each country characteristic to decile rankings (scaled between 0 and 1) by sorting them in ascending order into 10 groups. As explained in regression (2) of section 4.1, we use the time-series average ranking of each country characteristic during the previous five years (i.e., year *t-5* to year *t-1*) to match with the forecast dispersion of year *t*. We explain the choices and definitions of these country characteristics when appropriate in the remaining part of the paper. Table 3 reports the Spearman correlations among these country characteristics based on their time-series average rankings over the whole sample period.

4.1 Information environment and the dispersion effect across countries

We start our investigation with a country's information environment. This is because the main variable causing the dispersion effect (i.e., forecast dispersion) is likely to be affected by information environment. Furthermore, as explained later, information environment is predicted to have a systematic and potentially different impact on the strength of the dispersion effect under each of the three explanations. We follow Bushee and Friedman (2016) to construct a country-year panel of information environment using the CIFAR index and the World Economic Forum's Global Competitiveness Report (GCR). For 1990 – 1994, we use the 1990 CIFAR values, as reported in La Porta et al. (1998). For 1995 – 1998, we use the 1995 CIFAR values, obtained from Bushman et al. (2004). The 1990 (1995) CIFAR index is created by examining and rating companies' 1990 (1995) annual reports on their inclusion and omission of 90 items. These indexes have been widely used in prior studies as a proxy for a country's information environment (e.g., La Porta et al. 1998, Bhattacharya et al. 2003, Bushman et al. 2004), but they are not available after 1995. Since 1999, the annual GCR has included data on either the quality of disclosure or accounting standards based on the extensive Executive Opinion Survey. [12] The survey data have also been used in previous literature (e.g., Gelos and Wei 2005, Jin and Myers 2006, Bushee and Friedman 2016). Hence, from 1999 to 2012, we use the annual GCR score as a proxy for information environment. In order to ensure comparison across years, we transform the values of the CIFAR index or GCR score into decile rankings (scaled between 0 and 1) each year. A higher ranking indicates greater information transparency. The correlation matrix in Table 3 shows that across countries, the Spearman correlation between the average ranking of information environment and the average ranking of forecast dispersion is -0.454 (*pvalue* = 0.026 in unreported result), suggesting that forecast dispersion is generally higher in countries with more opaque information environments.

We then examine the impact of information environment on the dispersion effect across countries. As explained in the introduction, both the difference-in-opinion explanation and the parameter-risk explanation predict a stronger dispersion effect in countries with more uncertain information

[12] The GCRs in 1999 and 2000 report the average country-level response to the question "The level of financial disclosure is extensive and detailed (1 = strongly disagree; 7 = strongly agree)." From 2002 onwards, the GCR reports the average country-level response to the following question: "In your country, how would you assess financial auditing and reporting standards regarding company financial performance? (1 = extremely weak; 7 = extremely strong)." This survey question is not available in the 2001 GCR, so we extend the GCR score in 2000 to 2001.

environments. The analyst-incentive explanation also suggests that a country's information environment would have a systematic impact on the dispersion effect, but the directional prediction is uncertain according to a model that we build on this explanation (presented in the appendix).

Similar to Scherbina (2005), this model extends DMS's (2002) and Scherbina's (2008) analyses on self-censoring to consider analysts' choice between self-censoring and adding an optimistic bias to their true forecasts and the resulting dispersion-bias relation. The model also examines how this choice varies with the degree of analysts' reputational concerns across countries, which enables us to predict how the dispersion-bias relation and the dispersion effect vary across countries.

In the model, we assume that the firm manager will penalize severely those analysts who issue forecasts that are some certain standard deviations below the mean of the underlying distribution of analysts' forecasts (henceforth the manager's threshold forecast). Scherbina (2005) cites the risk of being cut off from inside sources of information and losing one's livelihood as an example of the penalty. We further assume that analysts are not rewarded for reporting optimistic forecasts above the threshold forecast. Consequently, when an analyst's true earnings forecast is lower than the manager's threshold forecast, she has two choices: (1) adding an optimistic bias to her true forecast to report the manager's threshold forecast; and (2) self-censoring her low true forecast. Each choice carries a cost. Adding an optimistic bias generates reputational loss from issuing an incorrect forecast, creating forecast error. Self-censoring may create a temporary loss of clients and perhaps also the erosion of good rapport with the manager, who may view self-censoring analysts as less cooperative than those who choose to add an optimistic bias. Unlike adding an optimistic bias, self-censoring does not damage reputation. Consequently, in countries where analysts have greater reputational concerns, more analysts with low true forecasts will choose self-censoring over adding an optimistic bias. As self-censoring generates a greater upward bias in the mean reported forecast than reporting the manager's threshold forecast, more self-censoring would lead to a greater upward bias. In the appendix we show that the upward bias is larger the more dispersed the distribution of analysts' *underlying* forecasts and that the dispersion in analysts' *underlying* forecasts and the dispersion in analysts' *reported* forecasts are positively related. Together, these arguments imply that in countries where analysts have greater reputational concerns, there would be a stronger positive relation between the dispersion in analysts' reported forecast and upward bias in the mean reported forecast (i.e., the dispersion-bias relation) and hence a stronger dispersion effect.

Analysts' reputational concerns become more important where the demand for analyst forecasts is higher, because with higher demand, the rewards for gaining reputation are more likely to outweigh the costs of gathering and processing information (Barniv et al. 2005). Consequently, how a country's information environment affects the dispersion effect depends on its impact on investor demand for analyst forecasts. On the one hand, in countries with more opaque information environments, fewer investors may be willing to participate in the stock market due to the psychological phenomenon of uncertainty aversion (e.g., Dow and Werlang 1992, Chen and Epstein 2002, Knox 2003, Easley and O'Hara 2009), which leads to lower demand for analyst forecasts. On the other hand, analysts might be the only information source for investors in countries with more opaque information environments, which leads to greater demand for analyst forecasts.

As a result, it is an empirical question whether the dispersion effect will be stronger or weaker in countries with more opaque information environments. If it is stronger, the results are consistent with all three explanations. If it is weaker, the results favor the analyst-incentive explanation over the other two explanations.

We use the following Fama-MacBeth (1973) cross-sectional regression (2) to examine the impact of information environment on the dispersion effect across countries. The specification is the same as the one used by McLean et al. (2009) in their investigation of the determinants of cross-country differences in the share issuance effect.[13]

$$RET_{i,j,t+1} = \beta_0 + \beta_1 DISP_{i,j,t} + \beta_2 LOGMV_{i,j,t} + \beta_3 LOGBM_{i,j,t} + \beta_4 BMDUM_{i,j,t} + \beta_5 MOM_{i,j,t} + \beta_6 MOMDUM_{i,j,t} + \beta_7 DISP_{i,j,t} \times CHAR_{j,t} + \beta_8 CHAR_{j,t} + \varepsilon_{i,j,t+1}. \quad (2)$$

$RET_{i,j,t+1}$ is the return of stock i in country j in month $t+1$. $CHAR_{j,t}$ denotes the characteristic of country j in month t. It is calculated as country j's average ranking in this characteristic during the previous five years before the year in which month t resides. For example, for month t in 1996, $CHAR_{j,t}$ is the time-series average of the yearly ranking of a country characteristic, such as information environment, from 1991 to 1995 for country j. The definitions of the other explanatory variables are the same as those in regression (1). As Table 1 shows, U.S. stocks account for 42.1% of our whole sample, so U.S. stocks are likely to exert a great influence on the empirical results. In order to make sure that our cross-country results are not driven by U.S. stocks, we focus on non-U.S. stocks when conducting cross-country analyses in sections 4 – 6 and section 8. In robustness tests, we conduct all these analyses on a sample including U.S. stocks, and our conclusions do not change.[14]

The result is reported under "*Information Environment*" in Table 4. The coefficient on *DISP* × *CHAR* can be interpreted as the marginal change in the slope of the *DISP* coefficient per unit change in *CHAR*, and it is our main coefficient of interest. We find that the coefficient on *DISP* × *CHAR* is negative and significant, suggesting that the negative relation between forecast dispersion and future stock returns (i.e., the dispersion effect) is stronger (weaker) in countries with more transparent (opaque) information environments. Hence, this result supports the analyst-incentive explanation over the difference-in-opinion and parameter-risk explanations.

[13] Please refer to section 5.2.2 in McLean et al. (2009).

[14] Results based on a sample including U.S. stocks are available on request.

4.2 Other country characteristics

In this section, we investigate how the dispersion effect is affected by other country characteristics which, unlike information environment, have less ambiguous effects on investor demand for analyst forecasts.

Investor demand for analyst forecasts should be higher in countries with more developed stock markets. A more developed stock market has fewer trading obstacles. This not only can encourage a larger population to participate in the stock market but also can enhance trading activities among existing investors, which in turn increases demand for analyst forecasts. Following previous literature (e.g., Levine and Zervos 1998, La Porta et al. 2006, McLean et al. 2009, Titman et al. 2013), we use the ratio of stock market capitalization to gross domestic product (GDP) (*Mktcap*) as a proxy for stock market development. We retrieve the annual *Mktcap* for each country from 1990 to 2012 from the World Development Indicator provided by the World Bank at http://www.worldbank.org.

Investor protection should also have a positive impact on investor demand for analyst forecasts. In countries with stronger investor protection, investors believe that they are less likely to be expropriated by insiders, which not only can encourage more investors to participate in the stock market, but also can encourage existing investors to actively seek information for trading purposes (La Porta et al. 1997, Lins and Warnock 2004, Giannetti and Koskinen 2005, Giannetti and Simonov 2006). This in turn increases investor demand for analyst forecasts. Our proxy for investor protection is a country's legal origin (*Law*). La Porta et al. (1998) show that common law countries tend to have stronger investor protection than civil law countries. We obtain this information from Professor Andrei Shleifer's website at http://scholar.harvard.edu/shleifer/publications (Djankov et al. 2008).

Investor demand for analyst forecasts would be higher in countries with fewer capital controls (i.e., greater capital openness). Removing capital controls in a country can encourage foreign investment, including investment in the country's equity market, which can in turn increase demand for analyst forecasts. We construct a country-year panel of capital control in the following way. For 1990 – 1998, we use the annual capital control measure in Miniane (2004), which can be downloaded at https://www.imf.org/External/Pubs/FT/staffp/2004/02/miniane.htm.[15] Since a greater value in Miniane (2004) indicates greater capital control, we use (1− raw value) to transform the raw values downloaded from Miniane (2004). We denote this variable as *Miniane*. Since 1999, GCR has also reported the average country-level response to the following survey question: "Foreign ownership of companies in your country is (1 = rare, limited to minority stakes, and often prohibited in key sections, 7 = prevalent and encouraged)." We use the annual GCR score as a proxy for capital openness from 1999 to 2012 and

[15] Miniane's (2004) capital control measure is available until 2000 and for 21 countries in our sample. Hence, starting from 1999, we use GCR score as a proxy for capital control. GCR scores are available for all countries in our sample.

denote it as *GCR_CO*. A higher value indicates greater capital openness irrespective of whether *Miniane* or *GCR_CO* is used as our proxy.

Finally, investor demand for analyst forecasts should also be higher in countries where investors exhibit more intense usage of analyst forecasts. We measure the intensity of forecast usage in a country by estimating the average price reaction to analysts' earnings forecast revisions, that is, earnings response coefficient (*ERC*) as defined below. For each country *j* in year *y*, we run the following regression (3) based on all current fiscal-year annual earnings forecast revisions issued by individual analysts in this year. We exclude those forecasts issued during the 10 days around an earnings announcement in order to ensure that our *ERC* estimate is not contaminated by the price reaction to actual earnings announcements.

$$Abret_{i,t} = \beta_0 + \beta_1 FREV_{i,t} + \beta_k Control^k_{i,t} + \varepsilon_{i,t}. \quad (3)$$

$Abret_{i,t}$ is average daily abnormal stock return (in percent) during the 5 days ($t - 2$, $t + 2$) around a forecast revision issued for stock *i* on date *t*. Daily abnormal stock return is calculated as stock *i*'s return minus the corresponding value-weighted market return of the country where stock *i* is primarily traded. $FREV_{i,t}$ denotes forecast revision, calculated as the forecast issued by an individual analyst for stock *i* at date *t* minus this analyst's previous forecast for the same stock-fiscal year, scaled by the absolute value of the latter. We follow previous studies (e.g., Stickel 1991, Gleason and Lee 2003) to use an analyst's own prior forecast, instead of prior consensus forecast, as the benchmark to calculate forecast revision because these studies show that the former is a better benchmark than the latter.[16] The set of control variables ($Control^k$) includes *LOGMV, LOGBM, MOM, BMDUM, MOMDUM* (as defined in regression (1)) at the end of month prior to the month in which date *t* resides. $Control^k$ also includes the average daily abnormal return (*AVRET)* and the number of days with zero return (*NZERORET*) during the past 50 days (from $t - 52$ to $t - 3$) to control for a stock's return behavior during the days without forecast revisions. In addition, $Control^k$ includes the number of days since this analyst's prior forecast (*PREINTERVAL*) and the number of days until the actual earnings announcement date (*POSTINTERVAL*) to control for the effect of time horizon. Firm fixed effect is also included to control for any unobservable firm effect. Except the dummy variables, the explanatory variables are winsorized within each country at the top and bottom 1%. We require at least 20 observations in a country-year regression. The coefficient on *FREV* (β_1) captures the sensitivity of stock returns to analysts' earnings forecast revisions, which is our *ERC* estimate.

We apply the same regression as in our investigation of information environment (that is, regression (2)) to the other country characteristics discussed above. That is, we match the average decile ranking (scaled between 0 and 1) of a country characteristic from year $y - 5$ to $y - 1$ with the forecast

[16] In unreported results, we find that the coefficient on *FREV* (β_1) is greater when *FREV* is calculated based on an analyst's own prior forecast than on the prior consensus forecast (0.10 versus 0.06 for the non-U.S. sample, and 0.43 versus 0.29 for the U.S. sample). This result confirms the findings of previous studies that the former is a better benchmark than the latter.

dispersion in year y. The results are reported in Table 4. The significantly negative coefficients of $DISP \times CHAR$ in all columns indicate that in countries with more developed stock markets, stronger investor protection, greater capital openness, and more intense usage of analysts' earnings forecasts, the negative relation between forecast dispersion and future stock return is stronger. Taken together, these results suggest that in countries where investor demand for analyst forecasts is higher, the dispersion effect is stronger.[17] Since analysts' reputational concerns increase with investor demand for analyst forecasts, these results are consistent with the prediction from our reputational model, thus providing support for the analyst-incentive explanation.

5. Determinants of cross-country differences in the dispersion-bias relation

One unique prediction of the analyst-incentive explanation is a positive dispersion-bias relation. It is through this positive dispersion-bias relation that the dispersion effect ensues. This suggests for each result concerning the dispersion effect we have documented above, there should be a parallel result concerning the dispersion-bias relation.

5.1 The dispersion-bias relation in the international markets

DMS (2002) document a strong positive dispersion-bias relation in the U.S., consistent with the analyst-incentive explanation. We test whether this positive dispersion-bias relation extends to the international markets using the following regression:[18]

$$BIAS_{i,t} = \beta_0 + \beta_1 DISP_{i,t} + \beta_2 LOGMV_{i,t} + \beta_3 LOGBM_{i,t} + \beta_4 BMDUM_{i,t} + \beta_5 MOM_{i,t} + \beta_6 MOMDUM_{i,t} + \varepsilon_{i,t}. \quad (4)$$

$BIAS_{i,t}$ is bias in the mean reported forecast for stock i in month t, which is measured as analysts' mean reported earnings-per-share forecast for stock i in month t minus the corresponding actual earnings-per-share announced in the future, scaled by the absolute value of the latter. The definitions of the explanatory variables are the same as those in regression (1). As both forecast dispersion (*DISP*) and forecast bias (*BIAS*) of a stock are likely to be persistent across time, the time-series correlation in the error term is likely to be severe, which renders Fama-MacBeth an inappropriate method in this analysis of dispersion-

[17] As *ERC* measures how efficiently investors process the information contained in analysts' forecast revisions, a market with larger *ERC* would be considered more efficient. Table 3 shows that *ERC* and the proxy for stock market development are highly correlated, suggesting that a more efficient market is also more developed. Hence, the two results that the dispersion effect is stronger in countries with more efficient markets and also in countries with more developed markets complement each other.

[18] In unreported tables (available on request), we also use the portfolio method (as described in section 3.1) to examine the dispersion-bias relation. Specifically, for each country, we calculate the average upward bias in the mean reported forecast (*BIAS*) of each dispersion quintile. We find that the *BIAS* differential between D5 and D1 is positive and significant in all countries we examine.

bias relation.[19] Therefore, we use pooled regression and calculate test statistics based on standard errors clustered by both stock and calendar year when the mean forecasts are reported,[20] using the two-way clustering method in Thompson (2011). The second column of Table 5 reports the regression result, which shows a strong positive relation between *DISP* and *BIAS*, confirming the existence of a positive dispersion-bias relation in the international markets.

5.2 Country characteristics and the dispersion-bias relation across countries

In this section, we test whether the dispersion-bias relation is stronger in countries where investor demand for analyst forecasts is higher, using the following regression:

$$BIAS_{i,j,t} = \beta_0 + \beta_1 DISP_{i,j,t} + \beta_2 LOGMV_{i,j,t} + \beta_3 LOGBM_{i,j,t} + \beta_4 MOM_{i,j,t}$$
$$+ \beta_5 BMDUM_{i,j,t} + \beta_6 MOMDUM_{i,j,t} + \beta_7 DISP_{i,j,t} \times CHAR_{j,t} + \beta_8 CHAR_{j,t} + \varepsilon_{i,j,t}. \quad (5)$$

The specification of regression (5) is similar to that of regression (2), except that the dependent variable is replaced with forecast bias in the current month (*BIAS*) and that it is a pooled regression. The results are reported in columns 3 – 7 of Table 5. For all country characteristics, we find that the coefficients on *DISP* × *CHAR* are significantly positive, suggesting that the positive dispersion-bias relation is stronger in countries where investor demand for analyst forecasts is higher. Hence, these results provide further support for the analyst-incentive explanation.

6. Forecast accuracy as a proxy for analysts' reputational concerns

In this section, we examine how forecast accuracy affects the dispersion effect across countries. Analysts build up their reputations by issuing accurate forecasts (Scherbina 2008). Higher demand for analyst forecasts contributes to greater reputational concerns, which are manifested in greater forecast accuracy. Hence, forecast accuracy is a more direct and precise measure of analysts' reputational concerns than are proxies of demand for analyst forecasts. According to our reputational model, we expect to find a stronger dispersion effect and a stronger dispersion-bias relation in countries exhibiting greater forecast accuracy. Furthermore, we expect forecast accuracy to greatly reduce, if not subsume, the explanatory powers of the country characteristics affecting investor demand for analyst forecasts in a horse race test.

We calculate the average forecast accuracy for country *j* in year *y* based on all stock-month mean reported forecasts whose corresponding earnings are announced in year *y*. This is to ensure that the accuracy of each forecast is known in year *y* and hence there is no look-ahead bias. Forecast accuracy of each stock-month is calculated as (-1) multiplied by forecast error, which is the absolute value of *BIAS*.

[19] Because the time series correlation exists within both the dependent variable and the independent variable, the Fama-MacBeth cross-sectional regression method is not appropriate in this estimation (Peterson 2009).

[20] We tried three variations of two-way clustering: (1) by stock and calendar month, (2) by stock and calendar year, and (3) by stock and fiscal year. We chose the second method because it results in the most conservative test statistics.

As with other country characteristics, each year, we transform the values of country-level forecast accuracy to the decile rankings (scaled between 0 and 1). Table 3 shows that across countries, the average ranking of forecast accuracy is significantly positively correlated with the average rankings of all country characteristics proxying for demand for analyst forecasts, consistent with our argument above that these two are linked by analysts' reputational concerns.

We first use regression (2) to examine the impact of forecast accuracy on the dispersion effect across countries. As before, we match the average ranking of country-level forecast accuracy from year *y – 5 to y – 1* with forecast dispersion in year *y*. Results are reported in Panel A of Table 6. The second column (under "*Forecast Accuracy*") shows a significantly negative coefficient on *DISP* × *Forecast Accuracy*, suggesting that the dispersion effect is stronger in countries with higher forecast accuracy. More interestingly, when we include in the regression both *DISP* × *Forecast Accuracy* and *DISP* × *CHAR*, where *CHAR* represents various country characteristics proxying for investor demand for analyst forecasts, we find that the coefficient on *DISP* × *Forecast Accuracy* remains negatively significant, while the coefficient on *DISP* × *CHAR* loses its significance under all proxies.

We then use regression (5) to examine the impact of *Forecast Accuracy* on the dispersion-bias relation across countries and find parallel results, which are reported in Panel B of Table 6. Specifically, we first find a significantly positive coefficient on *DISP* × *Forecast Accuracy* when examining forecast accuracy alone. We also find that under all country characteristics except investor protection, *DISP* × *CHAR* loses its significance or changes to the wrong sign when it's included in the regression along with *DISP* × *Forecast Accuracy*. In the case of investor protection, the magnitude of the coefficient on *DISP* × *CHAR* is reduced from 0.13 to 0.06 after we include *DISP* × *Forecast Accuracy* in the regression. Taken together, the results in Table 6 provide strong evidence supporting our reputational model and the analyst-incentive explanation.[21]

7. A natural experiment: The Asian financial crisis of 1997−98

In sections 5 – 6, we examined how the strength of the dispersion effect and the strength of the dispersion-bias relation vary with country characteristics. However, there is concern that the country characteristics that we believe affect investor demand for analyst forecasts may simply capture the effects of some unobservable variables (the omitted variable problem). To address this concern, we use the 1997−98 Asian financial crisis as a natural experiment to conduct difference-in-differences tests. During the crisis, Thailand, South Korea and Indonesia turned to IMF for help. In return, these countries followed IMF prescriptions for recovery, including opening up their financial markets to foreigners (Kaplan and Rodrik 2001), which we expect to increase the demand for analyst forecasts for stocks traded in these

[21] In unreported tables (available on request), we find that in the U.S. market, both the dispersion-bias relation and the dispersion effect are stronger among firms for which analysts issue more accurate forecasts.

countries and thus intensify analysts' reputational concerns. Malaysia took a drastically different approach. It imposed sweeping capital controls in September 1998. One of the essential capital controls was prohibiting the repatriation of portfolio funds for 12 months (Jomo 2004). These controls resulted in an exogenous negative shock to market openness as well as portfolio outflows and inflows in Malaysia (Dornbusch 2001). This suggests that after the controls were imposed, the interest in transacting Malaysian stocks would decrease, which in turn implies a decrease in the demand for analyst forecasts and a decline in analysts' reputational concerns in Malaysia. The end result would be a weaker dispersion effect and a weaker bias-dispersion relation in Malaysia after the crisis, relative to those in South Korea and Thailand, according to the prediction of our reputational model.

We conduct a sequence of difference-in-differences tests. We first test whether the price reaction to analysts' forecast revisions, *ERC*, which measures investor demand for analyst forecasts, decreases in Malaysia post crisis, relative to *ERC* in Thailand and South Korea. Indonesia is not in our sample as it does not meet our sample selection criteria (described in the online appendix). We use the following regression on a sub-sample of individual forecast revisions used in regression (3):

$$Abret_i = \beta_0 + \beta_1 FREV_i + \beta_2 FREV_i \times TREAT_i + \beta_3 FREV_i \times POST_i + \beta_4 FREV_i \times POST_i \times TREAT_i$$
$$+ \beta_5 TREAT_i + \beta_6 POST_i + \beta_7 POST_i \times TREAT_i + \beta_k Control^k_i + \varepsilon_i. \quad (6)$$

We define $TREAT_i$ as a dummy variable, which is equal to 1 if a stock is traded in Malaysia (treatment sample) and 0 if it is traded in Thailand or South Korea (control sample); and $POST_i$ as a dummy variable, which is equal to 1 if the observation is in 1999, the year after the crisis (based on the forecast revision date) and 0 if it is in 1996, the year before the crisis. The dependent variable *Abret* is the average daily abnormal return around a forecast revision, and *FREV* denotes forecast revision, as in regression (3). The set of control variables ($Control^k$) in regression (6) includes all the control variables in regression (3) and also the interactions of each control variable with *POST* and *TREAT*, e.g., *LOGMV* × *TREAT, LOGMV* × *POST, LOGMV*× *POST* × *TREAT* (we use similar sets of interactions for other control variables). We also control for time fixed effect based on the forecast revision date. Test statistics are based on standard errors clustered by both stock and analyst. The results are reported in Table 7. For simplicity, we omit the coefficients on the control variables ($Control^k$) in Table 7.

The coefficient on $FREV_i \times TREAT_i$ can be interpreted as the difference in *ERC* between the treatment sample and the control sample before the crisis. The coefficient on $FREV_i \times POST_i$ can be interpreted as the difference in *ERC* before and after the crisis in the control sample. Our main variable of interest is the coefficient on $FREV_i \times POST_i \times TREAT_i$, which captures the difference-in-differences of *ERC* between the treatment sample and the control sample across the crisis. The results in Panel A of Table 7 show that it is significantly negative, suggesting that *ERC* decreases in Malaysia after the crisis, relative to *ERC* in South Korea and Thailand.

We then use the regression below to test the difference-in-differences in forecast accuracy (a proxy for analysts' reputational concerns). The sample is the subset of our main sample used in regression (1).

$$ACCURACY_i = \beta_0 + \beta_1 TREAT_i + \beta_2 POST_i + \beta_3 POST_i \times TREAT_i + \beta_k Control^k_i + \varepsilon_i. \quad (7)$$

ACCURACY denotes the accuracy of monthly mean reported forecast, as defined in section 6. In both regression (7) and the following regression (8), *POST* (either 0 or 1) is defined based on the calendar year in which the mean forecast is reported. $Control^k$ includes all the control variables in regression (1). Test statistics are based on standard errors clustered by both stock and calendar month. The result in Panel B of Table 7 shows a significantly negative coefficient on *POST* × *TREAT*, suggesting that the forecast accuracy in Malaysia decreases after the crisis, relative to that in Thailand and South Korea.

The results above suggest that the Asian financial crisis induces a negative exogenous shock to investor demand for analyst forecasts and analysts' reputational concerns in Malaysia. Next, we proceed to test whether this shock results in a weaker dispersion effect and a weaker dispersion-bias relation in Malaysia as predicted by the reputational model. We run the following regression on the subset of our main sample used in regression (1) as well:

$$RET_i \text{ (or } BIAS_i) = \beta_0 + \beta_1 DISP_i + \beta_2 DISP_i \times TREAT_i + \beta_3 DISP_i \times POST_i + \beta_4 DISP_i \times POST_i \times TREAT_i$$
$$+ \beta_5 TREAT_i + \beta_6 POST_i + \beta_7 POST_i \times TREAT_i + \beta_k Control^k_i + \varepsilon_i. \quad (8)$$

$Control^k$ in regression (8) includes all the control variables in regression (1) and also the interactions of each control variable with *POST* and *TREAT*. The interpretations of the coefficients of variables in regression (8) are similar to those in regression (6). When the dependent variable is *RET*, the coefficient on *DISP*× *POST* × *TREAT* is positive and significant, suggesting that the negative relation between forecast dispersion and future stock return (i.e., the dispersion effect) becomes weaker in Malaysia, relative to Thailand and South Korea, after the crisis. When the dependent variable is *BIAS*, the coefficient on *DISP* × *POST* × *TREAT* is negative and significant, suggesting that the positive relation between forecast dispersion and upward bias in the mean reported forecast (i.e., the dispersion-bias relation) becomes weaker in Malaysia relative to Thailand and South Korea after the crisis.

Overall, this natural experiment provides evidence confirming that it is investor demand for analyst forecasts and hence analysts' reputational concerns that causes the dispersion-bias relation and the dispersion effect. This finding thus alleviates the concern that the cross-country results presented earlier are caused by omitted variables.

8. Self-censoring bias and the dispersion effect across countries

Under pressure from corporate managers, analysts with low true forecasts choose either to add an optimistic bias to their true forecasts or to self-censor. Both activities contribute to the upward bias in the mean reported forecast, which is *BIAS* as defined in section 5.1. Our reputational model shows that in countries where analysts care more about their reputations, more analysts will choose self-censoring over adding an optimistic bias, which suggests that *self-censoring bias* would have a greater contribution to *BIAS* in these countries. Hence, we expect both a stronger dispersion effect and a stronger dispersion-bias relation in countries where *self-censoring bias* has a greater contribution to *BIAS*.

We calculate self-censoring bias using the formula of Scherbina (2008) as follows:

$$\textit{Self-censoring bias} = EPS - \frac{N*EPS+missing*(EPS^{min}-0.01)}{N+missing}\,. \quad (9)$$

EPS is the mean reported forecast, and EPS^{min} is the lowest outstanding forecast. *N* is the number of analysts who have issued forecasts, and *missing* is the number of missing analysts. If *N* is smaller than the number of analysts three months ago, then *missing* is the decreased number of analysts. If *N* is greater than or equal to the number of analysts three months ago, then *missing* is 0, which in turn indicates that *self-censoring bias* is 0.

We measure the contribution of self-censoring to upward bias in the mean reported forecast in a country using the ratio (*Ratio*) of average *self-censoring bias* to average *BIAS* in this country. Specifically, for each mean reported forecast, we calculate a *BIAS* and a *self-censoring bias*. As with *BIAS*, we scale *self-censoring bias* by the absolute value of actual earnings-per-share. To ensure a level comparison of the number of analysts over time in calculating *self-censoring bias*, we require that in both month *t* where the mean *EPS* forecast is reported and month *t – 3*, there are at least two analysts. Both *BIAS* and *self-censoring bias* are winsorized at the 1st and 99th percentiles in this country. We calculate an average *self-censoring bias* and an average *BIAS* for country *j* in year *y* based on all available stock-month mean reported forecasts whose corresponding actual earnings are announced in year *y* so that there is no look-ahead bias. A country-year *Ratio* is calculated as *self-censoring bias* divided by *BIAS*. We regard *Ratio* as missing if average *BIAS* is negative for a country-year.[22] A higher *Ratio* indicates that analysts' self-censoring has a greater contribution to the upward bias in the mean reported forecast.

Table 3 shows that the time-series average ranking of *Ratio* and average ranking of *Forecast Accuracy* are positively correlated across countries at 37.4% (*pvalue* = 0.072 in unreported result), suggesting that self-censoring has a greater contribution to upward bias in the mean reported forecast in countries where analysts have greater reputational concerns. *Ratio* is also positively correlated with all the country characteristics proxying for investor demand for analyst forecasts, suggesting that analysts are more likely to choose self-censoring as demand for their forecasts increases.

We then examine whether the dispersion effect and the positive dispersion-bias relation are both stronger in countries where *Ratio* is higher. We use regression (2) and regression (5) for each of these two tests, respectively, replacing *CHAR* by the average ranking of *Ratio* during the past five years. The results on the dispersion effect are reported in the last column of Table 4, while the results on the dispersion-bias

[22] 5 out of 538 country-years have negative average *BIAS*.

relation are reported in the last column of Table 5. We find that higher *Ratio* intensifies both the negative dispersion-return relation and the positive dispersion-bias relation. These results are consistent with our expectation.[23] They provide further support for our reputational model and hence for the analyst-incentive explanation.

9. Conclusion

In this study, we find robust evidence of the dispersion effect in the international markets. We further find that the dispersion effect is stronger in countries with more transparent information environments, more developed stock markets, stronger investor protection, greater capital openness, and more intense usage of analyst forecasts. We also document parallel results on the positive dispersion-bias relation in the international markets. Taken together, these results suggest that both the dispersion effect and the dispersion-bias relation are stronger in countries where investor demand for analyst forecasts is higher. As higher demand for analyst forecasts motivates analysts to build up their reputation, these results are consistent with the prediction from a reputational model that in countries where analysts have greater reputational concerns, analysts are more likely to choose self-censoring their low forecasts over adding an optimistic bias to their true forecasts, which leads to a stronger dispersion-bias relation and a stronger dispersion effect. As this reputational model is built on the analyst-incentive explanation, these results thus provide strong support for the analyst-incentive explanation.

The findings from a sequence of difference-in-differences tests based on a natural experiment involving the 1997−98 Asian financial crisis strengthen the results from our cross-country analyses. We find that across the crisis, both price reaction to analyst forecasts and forecast accuracy decrease in Malaysia, which imposed capital controls in response to the crisis, relative to those in South Korea and Thailand, which opened their financial markets to foreigners as required by IMF. These results suggest that after the crisis, investor demand for analyst forecasts and analysts' reputational concerns decrease in Malaysia, relative to South Korea and Thailand. Importantly, we find that after the crisis, both the dispersion effect and the positive dispersion-bias relation become weaker in Malaysia relative to the other two countries, which lends further support to our reputational model and the analyst-incentive explanation.

Overall, our results suggest that the analyst-incentive explanation deserves more attention than it has been given in explaining the dispersion effect.

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[23] When analysts self-censor their pessimistic forecasts, the number of analysts issuing forecasts decreases. Therefore, another prediction could be that the dispersion effect is stronger in countries where there is a greater decrease in the number of analysts issuing forecasts. Although we find that the average decrease in analyst coverage is significantly positively related with *Forecast accuracy* across countries, we do not find that it has a significant impact on the dispersion effect (although the sign is right). One possible reason is that many other factors contribute to the change in analyst coverage in any given country, making it an imprecise measure of analysts' self-censoring. In contrast, when we employ Scherbina's (2008) formula to calculate the forecast bias generated by the decrease in number of analysts, the resulting *Ratio* does indeed have a significant impact on the dispersion effect.

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Appendix: A model of analysts' incentives and reputational concerns

In this model, we first analyse analysts' incentives in a given country (similar to Scherbina (2005)), and then extend our analysis to an international setting where countries differ *only* in the degree of analysts' reputational concerns.

We assume that analysts' earnings forecast X is normally distributed with mean of μ and standard deviation of σ: $X \sim N(\mu, \sigma)$, where μ is the firm's mean expected earnings.[24] An individual analyst i's forecast x_i can then be expressed as: $x_i = \mu - k_i\sigma$, where $k_i \in (-\infty, +\infty)$.

As in Scherbina (2005), we assume that the firm manager does not like analysts who issue low forecasts and will penalize severely those who issue forecasts that are $\bar{k}$ ($\bar{k} > 0$) standard deviations below μ. That is, we assume $\mu - \bar{k}\sigma$ as the threshold forecast set by the firm manager, where $\bar{k}$ is the same for all firms. Analysts can be divided into two types: low forecast analysts with $k_i > \bar{k}$ and non-low forecast analysts with $k_i \leq \bar{k}$.

In order to avoid the severe penalty from the firm manager, a low forecast analyst i chooses between two actions: either deliberately adding an optimistic bias to her true forecast or self-censoring her forecast. Each action carries a cost. The cost of adding an optimistic bias is the cost of losing reputation due to the issuance of an inaccurate forecast, which is defined as:

$$\text{Cost of adding an optimistic bias} = \frac{R}{\sigma}((k_i - \bar{k})\sigma) = R\,(k_i - \bar{k}) \quad \text{(A1)}$$

This is because the forecast error perceived by analyst i is $(k_i - \bar{k})\sigma$ when she reports the threshold forecast of $\mu - \bar{k}\sigma$ rather than her true forecast of $\mu - k_i\sigma$. R is the degree of analysts' reputational concerns, which is positive and the same for all firms and all analysts in a given country. R is further scaled by σ to capture the idea that investors are more forgiving (hence, attaching a lower cost) to the forecast error if the forecast is for a firm which has more unpredictable earnings and a larger σ[25].

The cost of self-censoring does not involve the loss of reputation. Instead, it involves a temporary loss of clients and the erosion of good rapport with managers, who may view self-censoring analysts as less cooperative than those who choose to add an optimistic bias. We denote this cost as a constant of CS. Thus, cost of self-censoring = CS.

Low forecast analysts choose to add an optimistic bias when $R\,(k_i - \bar{k}) < CS$, and they choose to self-censor their forecasts when $R\,(k_i - \bar{k}) > CS$. They are indifferent between these two actions when

[24] Scherbina (2005) lays out the structure of public and private signals received by analysts for this assumption to hold.

[25] A larger dispersion in analysts' underlying forecasts (i.e., a larger σ) arises because the signals (both private and public) received by analysts are less precise, indicating that the earnings are more difficult to forecast.

$R\left(k_i - \bar{k}\right) = CS$, which occurs at $k^* = \frac{CS}{R} + \bar{k}$. Therefore, low forecast analysts choose to add an optimistic bias when $\bar{k} < k_i < k^*$; and they choose to self-censor when $k_i > k^*$.

As we focus on analysing the choice of low forecast analysts, we make a simplified assumption that non-low forecast analysts (those with $k_i \leq \bar{k}$) issue their true forecasts. The implied assumption is that analysts are not rewarded for issuing optimistic forecasts above the firm manager's threshold forecast of $\mu - \bar{k}\sigma$.

With this set up, analysts would report their forecasts X_{rep} in the following way:

$$X_{rep} = \begin{cases} X & if\ X \geq \mu - \bar{k}\sigma \\ \mu - \bar{k}\sigma & if\ \mu - k^*\sigma \leq X < \mu - \bar{k}\sigma \\ self - censored & if\ \ X < \mu - k^*\sigma \end{cases} \tag{A2}$$

Equation (A2) suggests that the distribution of all reported forecasts X_{rep} is a mixture of a discrete distribution and a left truncated normal distribution, with the discrete distribution being a constant of $\mu - \bar{k}\sigma$. The mean reported forecast $\bar{X}_{rep}$ is:

$$\bar{X}_{rep} = E(X_{rep} \mid X > \mu - k^*\sigma) = \int_{\mu-k^*\sigma}^{\infty} X_{rep} f\left(x \mid X > \mu - k^*\sigma\right) dx = \frac{\int_{\mu-k^*\sigma}^{\infty} X_{rep} f\left(x\right) dx}{\Phi(k^*)} \tag{A3}$$

Where $f(.)$ is the probability density function.

$$\begin{aligned} \int_{\mu-k^*\sigma}^{\infty} X_{rep} f\left(x\right) dx &= \int_{\mu-k^*\sigma}^{\mu-\bar{k}\sigma} (\mu - \bar{k}\sigma) f\left(x\right) dx + \int_{\mu-\bar{k}\sigma}^{\infty} x f\left(x\right) dx \\ &= (\mu - \bar{k}\sigma)\left(\Phi(k^*) - \Phi(\bar{k})\right) + \Phi(\bar{k})(\int_{\mu-\bar{k}\sigma}^{\infty} x f\left(x \mid X > \mu - \bar{k}\sigma\right) dx \\ &= (\mu - \bar{k}\sigma)\left(\Phi(k^*) - \Phi(\bar{k})\right) + \Phi(\bar{k})\left(\mu + \sigma\frac{\phi(\bar{k})}{\Phi(\bar{k})}\right) \end{aligned} \tag{A4}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the P.D.F. and C.D.F. of a standard normal distribution.

From (A3) and (A4), we have

$$\bar{X}_{rep} = (\mu - \bar{k}\sigma)\left(1 - \frac{\Phi(\bar{k})}{\Phi(k^*)}\right) + \mu\frac{\Phi(\bar{k})}{\Phi(k^*)} + \left(\sigma\frac{\phi(\bar{k})}{\Phi(k^*)}\right) \tag{A5}$$

The upward bias in the mean reported forecast *Bias* is:

$$Bias = \bar{X}_{rep} - \mu = (-\bar{k}\sigma)\left(1 - \frac{\Phi(\bar{k})}{\Phi(k^*)}\right) + \left(\sigma\frac{\phi(\bar{k})}{\Phi(k^*)}\right) \tag{A6}$$

The sensitivity of *Bias* to the standard deviation of underlying forecasts σ is:

$$\frac{\partial Bias}{\partial \sigma} = -\bar{k}(1 - \frac{\Phi(\bar{k})}{\Phi(k^*)}) + \frac{\phi(\bar{k})}{\Phi(k^*)} > 0 \quad \text{since } k^* > \bar{k} > 0 \tag{A7}$$

It can be shown that equation (A7) is positive for any $k^* \geq \bar{k} \geq 0$. Note that the standard deviation of the reported forecasts (σ_{rep}) increases with the standard deviation of the underlying forecasts (σ). This is because, as shown in equation (A2), X_{rep} can be described by a mixture of a discrete distribution which is a constant at $\mu - \bar{k}\sigma$ and a left truncated normal distribution with interval of $(\mu - \bar{k}\sigma, +\infty)$. As shown in Scherbina (2005), the standard deviation of the reported forecasts from the left truncated normal distribution is $\sigma\left(1-\bar{k}\frac{\varphi(\bar{k})}{1-\Phi(\bar{k})}\right)^{-1/2}$, which is an increasing function of σ. This, combined with the fact that the location of the discrete distribution (i.e., the lowest value of X_{rep}) becomes lower with a greater σ, suggests that σ_{rep} and σ are positively related, which can be written as $\sigma = \alpha\,\sigma_{rep}$ $(\alpha > 0)$. The sensitivity of $Bias$ to σ_{rep} (i.e., the dispersion-bias relation) can thus be expressed as:

$$\frac{\partial Bias}{\partial \sigma_{rep}} = \alpha \times \left(-\bar{k}\,(1-\frac{\Phi(\bar{k})}{\Phi(k^*)}) + \frac{\phi(\bar{k})}{\Phi(k^*)} \right) > 0 \tag{A8}$$

Next, we extend the above analysis to the international setting in which R differs across countries. Note that $\frac{\partial k^*}{\partial R} < 0$ because $k^* = \frac{cs}{R} + \bar{k}$. This suggests that in countries where analysts have greater reputational concerns, more analysts choose self-censoring over adding an optimistic bias. Thus, it is straightforward to show that:

$$\frac{\partial Bias}{\partial \sigma_{rep}\,\partial R} = \alpha \times \frac{\partial Bias}{\partial \sigma_{rep}\,\partial k^*} \times \frac{\partial k^*}{\partial R} = \alpha \times \frac{-\left(\bar{k}\Phi(\bar{k}) + \phi(\bar{k})\right)\phi(k^*)}{\Phi(k^*)^2} \times \frac{\partial k^*}{\partial R} > 0 \tag{A9}$$

Equation (A9) indicates that the positive dispersion-bias relation is stronger in countries where analysts have greater reputational concerns. To the extent that investors do not properly adjust the bias embedded in forecast dispersion, the positive dispersion-bias relation would translate to a negative relation between forecast dispersion and future stock return (i.e., the dispersion effect). Hence, the model predicts that the dispersion effect is stronger in countries where analysts have greater reputational concerns.

Table 1 Summary statistics

Our sample consists of data on individual stocks covered by at least two analysts and traded on the major exchanges in each of the 24 countries. "*Pct. of obs.*" is the percentage of observations for each country. "*No. of months*" is the number of months in the return history of each country over the sample period from Feb 1990 to Dec 2013. "*No. of stocks*" is the time series average of monthly number of stocks. "*Pct. of stocks with coverage>2*" is the time series average of monthly percentage of I/B/E/S stocks covered by at least two analysts. "*Pct. of stocks covered by I/B/E/S*" is the percentage of Datastream stocks covered by I/B/E/S. *COV*, *LOGMV*, *LOGBM*, *MOM*, and *DISP* are the time series averages of monthly median values of the number of analysts covering a stock, the natural logarithm of market value of equity, the natural logarithm of book-to-market ratio, the past six months' buy-and-hold stock return, and forecast dispersion. Forecast dispersion is calculated as the ratio of the standard deviation of analysts' current fiscal-year annual earnings-per-share forecasts (i.e., forecasts of forthcoming earnings-per-share) to the absolute value of the mean forecast.

Country (Stock Exchanges)	*Pct. of obs.*	*No. of months*	*No. of stocks*	*Pct. of stocks with coverage >2*	*Pct. of stocks covered by I/B/E/S*	*COV*	*LOGMV*	*LOGBM*	*MOM*	*DISP*
Australia (Australian)	3.2%	272	254	0.78	0.35	6.90	5.94	-0.44	0.06	0.08
Brazil (Sao Paulo)	0.8%	123	131	0.83	0.23	6.87	6.43	-0.27	0.06	0.22
Canada (Toronto)	4.4%	286	333	0.81	0.45	5.40	5.66	-0.35	0.04	0.14
China (Shanghai & Shenzhen)	2.9%	106	585	0.67	0.87	3.83	6.89	-1.03	0.11	0.09
France (Paris)	3.2%	279	248	0.76	0.50	7.42	6.37	-0.49	0.04	0.11
Germany (Frankfurt)	3.2%	280	242	0.74	0.43	7.84	5.88	-0.58	0.02	0.13
Hong Kong (Hong Kong)	3.2%	286	240	0.83	0.77	9.55	6.07	-0.16	0.05	0.11
India (Mumbai)	1.6%	149	226	0.72	0.78	6.10	6.24	-0.62	0.01	0.10
Italy (Milan)	1.4%	237	125	0.83	0.56	7.86	6.55	-0.29	0.00	0.16
Japan (Tokyo & JASDAQ)	10.2%	287	764	0.73	0.96	4.69	6.95	-0.37	0.00	0.10
Malaysia (Kuala Lumpur & MESDAQ)	2.0%	279	155	0.74	0.77	7.42	5.70	-0.42	0.06	0.12
Netherlands (Amsterdam)	0.9%	153	132	0.89	0.54	11.21	5.38	-0.46	0.05	0.08
Norway (Oslo)	0.5%	95	123	0.80	0.61	5.05	5.82	-0.31	0.05	0.18
Singapore (Singapore)	1.5%	256	123	0.79	0.78	8.66	5.96	-0.28	0.06	0.11
South Africa (Johannesburg)	1.0%	152	135	0.74	0.49	5.35	6.24	-0.48	0.05	0.07
South Korea (Korea & KOSDAQ)	2.5%	156	340	0.68	0.71	4.53	4.95	0.13	-0.01	0.23

Table 1 Continued

Spain (Madrid)	0.3%	71	105	0.91	0.54	12.67	6.39	-0.35	-0.04	0.12
Sweden (Stockholm)	1.3%	206	133	0.69	0.32	5.50	5.97	-0.65	0.07	0.12
Switzerland (Zurich)	1.6%	280	124	0.86	0.35	7.00	6.25	-0.45	0.05	0.11
Taiwan (Taiwan)	1.7%	232	161	0.68	0.63	4.16	6.45	-0.45	0.00	0.15
Thailand (Thailand)	0.9%	148	127	0.70	0.74	6.42	5.56	-0.51	0.06	0.12
Turkey (Istanbul)	1.0%	118	174	0.79	0.54	5.12	3.75	-0.02	0.09	0.27
U.K. (London)	8.6%	287	642	0.69	0.55	5.33	6.00	-0.60	0.05	0.06
U.S. (NYSE, AMEX & NASDAQ)	42.1%	287	3144	0.80	0.73	5.70	6.24	-0.61	0.04	0.05

Table 2 International dispersion effect

At the end of each month, we divide all stocks within each country into five portfolios based on forecast dispersion. D1 (D5) includes stocks with the lowest (highest) dispersion. After being assigned to portfolios, stocks are held for one month. D1 − D5 is the hedge portfolio that holds a long position in stocks of D1 and a short position in stocks of D5. The monthly return (in percentage) of each portfolio is calculated as the equal-weighted average of the returns of all of its stocks. Panel A reports the average monthly return of each dispersion quintile portfolio and that of the hedge portfolio for each non-U.S. country. FF3 alpha is the intercept from regressing the monthly returns of (D1 − D5) onto the local Fama-French three factors in each country. Panel B reports the non-U.S. aggregate portfolio returns and the U.S. portfolio returns. We construct two types of non-U.S. aggregate portfolios. The country-average dispersion portfolio equally weights each country-specific dispersion portfolio, as described in Panel A. The country-composite dispersion portfolio is weighted more toward countries with more stocks. Specifically, stocks in the top (bottom) quintile of forecast dispersion in each country are assigned to the "D5" ("D1") composite portfolio. FF3 alpha for country-average (country-composite) portfolio is the intercept from regressing the monthly returns of (D1− D5) onto the country-average (country-composite) Fama-French three factors. FF3 alpha of (D1− D5) for U.S. is based on the Fama-French (1993) three factors retrieved from Kenneth French's website. Panel C reports the results of the following Fama-MacBeth (1973) cross-sectional regressions among non-U.S. and U.S. stocks, respectively: $RET_{i,t+1} = \beta_0 + \beta_1 DISP_{i,t} + \beta_2 LOGMV_{i,t} + \beta_3 LOGBM_{i,t} + \beta_4 BMDUM_{i,t} + \beta_5 MOM_{i,t} + \beta_6 MOMDUM_{i,t} + \varepsilon_{i,t+1}$. *RET* is monthly stock return. *DISP*, *LOGMV*, *LOGBM*, and *MOM* are defined in Table 1. *BMDUM* is a dummy variable; if *LOGBM* is missing, then both *LOGBM* and *BMDUM* are assigned values of zero; otherwise *BMDUM* is set to one. *MOMDUM* is also a dummy variable; if *MOM* is missing, then both *MOM* and *MOMDUM* are assigned values of zero; otherwise, *MOMDUM* is set to one. The *t*-statistics (in parentheses) are based on Newey-West standard errors.

Panel A Portfolio return

Country	D1	D2	D3	D4	D5	D1 − D5	FF3 Alpha
Australia	1.32	1.13	1.09	0.72	0.02	1.30 (3.64)	1.00(3.51)
Brazil	1.22	1.13	0.76	0.70	0.19	1.03 (2.84)	0.95(2.73)
Canada	1.12	1.17	0.77	0.50	0.05	1.07 (3.26)	1.11(4.62)
China	1.86	2.13	1.94	2.20	1.88	-0.02 (-0.05)	0.32(1.08)
France	1.06	1.07	0.92	0.81	0.29	0.77 (3.79)	0.98(4.49)
Germany	0.79	0.70	0.78	0.40	-0.35	1.14 (4.44)	0.94(6.07)
Hong Kong	1.41	1.28	1.11	0.90	0.52	0.89 (4.06)	1.01(5.48)
India	0.90	0.83	0.47	0.10	-0.22	1.12 (2.43)	8.88(4.72)
Italy	0.68	0.49	0.40	0.17	-0.37	1.05 (6.37)	1.03(6.85)
Japan	0.23	0.31	0.29	0.29	0.16	0.07 (0.58)	0.25(1.64)
Malaysia	1.07	1.16	0.79	0.79	0.33	0.74 (3.53)	0.95(6.34)
Netherlands	1.44	1.53	1.23	1.12	0.43	1.01 (3.49)	0.85(3.11)
Norway	1.36	1.40	1.35	0.84	0.41	0.95 (2.69)	1.05(3.44)
Singapore	1.15	0.96	0.87	0.80	0.39	0.76 (3.63)	0.85(4.82)
South Africa	1.26	1.27	0.85	0.75	0.36	0.90 (3.28)	1.37(4.62)
South Korea	0.83	0.64	0.53	0.52	0.28	0.55 (2.63)	0.69(3.41)
Spain	0.36	0.16	-0.37	-0.30	-0.60	0.96 (2.08)	0.55(1.40)
Sweden	1.34	1.36	1.06	0.99	0.41	0.93 (2.63)	0.87(2.71)
Switzerland	1.05	1.01	0.92	0.80	0.65	0.40 (2.11)	0.46(2.60)

Table 2 Continued

Taiwan	0.78	0.56	0.53	0.44	0.03	0.75 (3.92)	1.02(5.44)	
Thailand	0.87	0.77	0.83	0.66	0.21	0.66 (1.73)	0.82(2.17)	
Turkey	2.74	2.99	2.47	2.70	2.86	-0.12 (-0.18)	0.00(0.01)	
U.K.	1.09	1.05	0.99	0.79	0.14	0.95 (3.69)	1.04(3.59)	
Panel B Aggregate portfolio return								
	D1	D2	D3	D4	D5	D1 − D5	FF3 Alpha	
Country-average	1.05	1.01	0.84	0.71	0.28	0.77 (6.12)	1.05 (6.17)	
Country-composite	0.91	0.89	0.76	0.62	0.18	0.73 (5.54)	1.29 (8.21)	
U.S.	1.23	1.19	1.19	1.10	0.90	0.33 (1.04)	0.72 (3.22)	
Panel C Fama-MacBeth regression								
Variable	*Estimate*	*t-statistic*	*Estimate*	*t-statistic*	*Estimate*	*t-statistic*		
INTERCEPT	0.57	(1.14)	0.00	(-1.16)	1.03	(1.40)		
DISP	**-0.38**	**(-5.97)**	**-0.36**	**(-7.12)**	**-0.43**	**(-2.83)**		
LOGMV	0.04	(1.22)	0.12	(4.30)	-0.07	(-1.30)		
LOGBM	0.58	(5.20)	0.60	(5.99)	0.13	(1.47)		
BMDUM	0.54	(4.08)	0.80	(8.32)	0.53	(2.83)		
MOM	0.73	(2.31)	0.91	(3.89)	0.35	(0.99)		
MOMDUM	-0.41	(-2.27)	-0.41	(-2.80)	-0.04	(-0.10)		
Country fixed effect	No		Yes					

Table 3 Country characteristics and their correlations

This table displays the country characteristics used in Tables 4 – 6. *Information Environment* is proxied by two country variables: *CIFAR* and *GCR*. The *CIFAR* index is created by examining and rating companies' 1990 (or 1995) annual reports on their inclusion and omission of 90 items. For 1990 – 1994, we use the 1990 *CIFAR* values, obtained from La Porta et al. (1998). For 1995 – 1998, we use the 1995 *CIFAR* values, obtained from Bushman et al. (2004). From 1999 onwards, we use the *GCR* score on either the quality of disclosure or accounting standards based on the World Economic Forum's extensive Executive Opinion Survey, which is reported in the annually published Global Competitiveness Report (GCR). *Forecast Dispersion* is defined in Table 1 (*DISP*). *Stock Market Development* is proxied by the ratio of stock market capitalization to gross domestic product (GDP) (*Mktcap*). We obtain annual *Mktcap* over the period of 1990-2012 from the World Bank at http://www.worldbank.org. *Investor Protection* is proxied by a country's legal origin (*Law*), which is equal to one if a country is of common law origin and zero if the country is of civil law origin. This information is obtained from Djankov et al. (2008). *Capital Openness* is proxied by two variables: *Miniane* and *GCR_CO*. For 1990 – 1998, we use the annual capital control measure in Miniane (2004) (*Miniane*), obtained at https://www.imf.org/External/Pubs/FT/staffp/2004/02/miniane.htm. From 1999 onwards, we use the GCR score (*GCR_CO*) based on the average country-level response to the survey question "Foreign ownership of companies in your country is (1 = rare, limited to minority stakes, and often prohibited in key sections, 7 = prevalent and encouraged)," obtained from the annually published Global Competitiveness Report. The extent to which investors use analysts' earnings forecasts (*Intensity of Forecast Usage*) is proxied by *ERC* (earnings response coefficient), which captures the average price response to analysts' earnings forecast revisions. For a country-year, we estimate *ERC* using the following regression based on all current fiscal-year annual earnings-per-share forecast revisions issued by individual analysts during this year (except those revisions issued during the 10 days around an actual earnings announcement) for stocks traded primarily in this country: $Abret_{i,t} = \beta_0 + \beta_1 FREV_{i,t} + \beta_k Control^k_{i,t} + \varepsilon_{i,t}$. $Abret_{i,t}$ is average daily abnormal stock return (in percent) during the 5 days (t – 2, t + 2) around a forecast revision issued for stock *i* on date *t*. Daily abnormal stock return is calculated as stock *i*'s return minus the corresponding value-weighted market return of the country where stock *i* is primarily traded. $FREV_{i,t}$ denotes forecast revision, calculated as the forecast issued by an individual analyst for stock *i* at date *t* minus this analyst's previous forecast for the same stock-fiscal year, scaled by the absolute value of the latter. The set of control variables ($Control^k$) includes *LOGMV, LOGBM, BMDUM, MOM, MOMDUM* (as defined Table 1) at the end of month prior to the month in which date *t* resides. It also includes the average daily abnormal return (*AVRET)* and the number of days with zero return (*NZERORET*) during the past 50 days (from t – 52 to t – 3). In addition, it includes the number of days since this analyst's prior forecast (*PREINTERVAL*), the number of days until the actual earnings announcement date (*POSTINTERVAL*) and firm fixed effect. The coefficient on *FREV* (β_1) measures the sensitivity of stock return to earnings forecast revision, which is our *ERC* estimate. We require at least 20 observations to estimate a country-year *ERC*. *Forecast Accuracy* for each country *j* in year *y* is measured by averaging the accuracy (*ACC*) of all monthly mean reported forecasts whose corresponding actual earnings are announced in year *y*. The accuracy of a mean reported forecast is measured as (-1) multiplied by forecast error, which is in turn measured as the absolute value of the ratio of the difference between the mean reported forecast and actual earnings-per-share to the latter variable. *Ratio* is the ratio of average *self-censoring bias* to average upward bias in the mean reported forecast in a country-year, which captures the contribution of self-censoring to the upward bias in the mean reported forecast. Specifically, for each stock-month mean reported forecast in a country, we first calculate a *BIAS* and a *self-censoring bias*. *BIAS* is the upward bias in the mean reported forecast, which is measured as monthly mean reported earnings forecast minus actual earnings-per-share, scaled by the absolute value of the latter variable. We use the formula of Scherbina (2008): *self-censoring bias* = $EPS - \frac{N*EPS+missing*(EPS^{min}-0.01)}{N+missing}$ to calculate the forecast bias generated by analysts' self-censoring. *EPS* is the mean reported earnings forecast, and EPS^{min} is the lowest outstanding forecast. *N* is the number of analysts who have issued forecasts, and *missing* is the number of missing analysts. If *N* is smaller than the number of analysts three months ago, then *missing* is the decreased number of analysts. If *N* is greater than or equal to the number of analysts three months ago, then *missing* is 0, which in turn indicates that *self-censoring bias* is 0. As with *BIAS*, we scale *self-censoring bias* by the absolute value of actual earnings-per-share. Both *BIAS* and *self-censoring bias* are winsorized at the 1^{st} and 99^{th} percentiles in a country. We then calculate a country-year *self-censoring bias* and a country-year *BIAS* by averaging all stock-month mean reported forecasts whose corresponding actual earnings are announced in the current year. A country-year *Ratio* is calculated as *self-censoring bias* divided by *BIAS*. Each year, we obtain the decile ranking of a country characteristic by sorting the raw values in ascending order into 10 groups and then scaling these rankings to be within the range of [0, 1]. This table shows the Spearman correlations among the country characteristics based on their time-series average decile rankings over the sample period from 1990 to 2012. *, **, and *** represent *pvalue* < 0.1, 0.01 and 0.001, respectively.

	Information Environment	*Forecast Dispersion*	*Stock Market Development*	*Investor Protection*	*Capital Openness*	*Intensity of Forecast Usage*	*Forecast Accuracy*
Forecast Dispersion	-0.454*						
Stock Market Development	0.699**	-0.612**					
Investor Protection	0.440*	-0.378*	0.595**				
Capital Openness	0.712***	-0.309	0.574**	0.147			
Intensity of Forecast Usage	0.591**	-0.791***	0.690**	0.592**	0.447*		
Forecast Accuracy	0.512**	-0.875***	0.660**	0.586**	0.340*	0.871***	
Ratio	0.136	-0.093	0.271	0.476*	0.240	0.291	0.374*

Table 4 Determinants of cross-country differences in the dispersion effect

This table reports the results of the following Fama-Macbeth (1973) regression: $RET_{i,j,t+1} = \beta_0 + \beta_1 DISP_{i,j,t} + \beta_2 LOGMV_{i,j,t} + \beta_3 LOGBM_{i,j,t} + \beta_4 BMDUM_{i,j,t} + \beta_5 MOM_{i,j,t} + \beta_6 MOMDUM_{i,j,t} + \beta_7 DISP_{i,j,t} \times CHAR_{j,t} + \beta_8 CHAR_{j,t} + \varepsilon_{i,j,t+1}$. The dependent variable is the return of stock *i* in country *j* in month *t+1*. $CHAR_{j,t}$ denotes a characteristic of country *j*, which is the average decile ranking (scaled to be within [0, 1]) of *CHAR* in country *j* during the past 5 years before the year in which month *t* resides. For example, for month *t* in 1996, $CHAR_{j,t}$ is the time-series average of the yearly decile ranking of *CHAR* from 1991 to 1995 for country *j*. *CHAR*s are country characteristics defined in Table 3. The definitions of other explanatory variables are the same as those in Table 2. *DISP* × *CHAR* is the interaction between *DISP* and *CHAR*. The *t*-statistics (in parentheses) are calculated based on Newey-West standard errors.

	Information Environment	*Stock Market Development*	*Investor Protection*	*Capital Openness*	*Intensity of Forecast Usage*	*Ratio*
INTERCEPT	0.38	0.62	0.34	0.49	-0.15	0.12
	(0.65)	(1.06)	(0.65)	(0.79)	(-0.26)	(0.22)
DISP	-0.01	-0.06	-0.24	-0.11	0.21	0.05
	(-0.07)	(-0.49)	(-4.08)	(-1.00)	(1.51)	(0.42)
LOGMV	0.04	0.05	0.05	0.04	0.05	0.05
	(1.18)	(1.48)	(1.72)	(1.07)	(1.50)	(1.59)
LOGBM	0.61	0.59	0.57	0.58	0.61	0.59
	(4.72)	(4.51)	(4.87)	(4.80)	(4.80)	(4.68)
BMDUM	0.54	0.56	0.54	0.50	0.59	0.59
	(3.76)	(3.71)	(3.90)	(2.97)	(3.90)	(4.08)
MOM	0.90	0.90	0.70	0.80	0.92	0.95
	(2.64)	(2.66)	(2.10)	(2.37)	(3.11)	(3.28)
MOMDUM	-0.36	-0.32	-0.40	-0.34	-0.25	-0.26
	(-2.05)	(-1.75)	(-2.32)	(-1.84)	(-1.51)	(-1.52)
DISP × CHAR	**-0.72**	**-0.63**	**-0.36**	**-0.57**	**-1.31**	**-1.00**
	(-2.95)	**(-2.79)**	**(-3.36)**	**(-2.81)**	**(-4.09)**	**(-4.05)**
CHAR	0.39	-0.15	0.32	0.31	1.10	0.63
	(1.06)	(-0.47)	(1.67)	(0.81)	(2.34)	(1.19)

Table 5 Determinants of cross-country differences in the dispersion-bias relation

This table reports the results of the following pooled regression: $BIAS_{i,j,t} = \beta_0 + \beta_1 DISP_{i,j,t} + \beta_2 LOGMV_{i,j,t} + \beta_3 LOGBM_{i,j,t} + \beta_4 BMDUM_{i,j,t} + \beta_5 MOM_{i,j,t} + \beta_6 MOMDUM_{i,j,t} + \beta_7 DISP_{i,j,t} \times CHAR_{j,t} + \beta_8 CHAR_{j,t} + \varepsilon_{i,j,t}$. $BIAS_{i,j,t}$ is the forecast bias of stock i in country j in month t, which is measured as the mean reported earnings forecast in month t for stock i minus actual earnings-per-share announced in the future, scaled by the absolute value of the latter variable. The explanatory variables are the same as those in Table 4. The second column reports the result *without* interacting *DISP* with a country characteristic (*CHAR*). The *t*-statistics (in parentheses) are calculated based on standard errors clustered by both stock and calendar year in which the mean forecast is reported.

		Information Environment	*Stock Market Development*	*Investor Protection*	*Capital Openness*	*Intensity of Forecast Usage*	*Ratio*
INTERCEPT	0.64	0.80	0.81	0.70	0.77	0.82	0.77
	(8.57)	(8.38)	(8.68)	(8.63)	(9.04)	(8.12)	(8.13)
DISP	**0.09**	0.00	-0.05	0.04	0.00	-0.01	-0.04
	(4.99)	(0.09)	(-1.00)	(1.69)	(0.00)	(-0.21)	(-1.18)
LOGMV	-0.06	-0.07	-0.06	-0.06	-0.06	-0.06	-0.06
	(-8.38)	(-9.86)	(-8.98)	(-9.32)	(-10.06)	(-8.38)	(-8.21)
LOGBM	0.03	0.02	0.02	0.02	0.02	0.02	0.02
	(2.51)	(1.37)	(1.75)	(1.85)	(1.45)	(1.32)	(1.85)
BMDUM	-0.07	-0.06	-0.07	-0.07	-0.07	-0.07	-0.07
	(-1.73)	(-1.20)	(-1.52)	(-1.60)	(-1.33)	(-1.46)	(-1.56)
MOM	-0.43	-0.42	-0.42	-0.42	-0.41	-0.42	-0.42
	(-10.00)	(-10.24)	(-9.63)	(-9.97)	(-9.75)	(-9.49)	(-9.40)
MOMDUM	0.17	0.27	0.22	0.22	0.24	0.21	0.18
	(5.79)	(8.61)	(9.42)	(9.16)	(8.95)	(9.19)	(9.31)
DISP × CHAR		**0.15**	**0.25**	**0.13**	**0.17**	**0.19**	**0.32**
		(2.12)	**(3.56)**	**(5.13)**	**(2.45)**	**(2.33)**	**(4.84)**
CHAR		-0.42	-0.37	-0.20	-0.33	-0.43	-0.30
		(-8.40)	(-8.06)	(-8.00)	(-9.88)	(-5.87)	(-4.63)

Table 6 Country-level forecast accuracy and cross-country differences in the dispersion effect and the dispersion-bias relation

Panel A examines the dispersion effect using the regression from Table 4, while Panel B examines the dispersion-bias relation using the regression from Table 5. As with *CHAR* in the regressions of Table 4 and Table 6, *Forecast Accuracy* is the average decile ranking of a country's forecast accuracy during the past five years before the year in which month *t* resides.

Panel A The dispersion effect						
	Forecast Accuracy	*Information Environment*	*Stock Market Development*	*Capital Openness*	*Investor Protection*	*Intensity of Forecast Usage*
INTERCEPT	-0.22	-0.40	-0.20	-0.27	-0.27	-0.46
	(-0.39)	(-0.75)	(-0.37)	(-0.46)	(-0.50)	(-0.77)
DISP	0.08	0.09	0.07	0.06	0.07	0.09
	(0.85)	(0.69)	(0.53)	(0.44)	(0.66)	(0.58)
LOGMV	0.06	0.06	0.07	0.06	0.07	0.06
	(2.28)	(2.49)	(2.49)	(2.41)	(2.48)	(2.42)
LOGBM	0.65	0.66	0.65	0.63	0.64	0.65
	(5.31)	(5.33)	(5.57)	(5.37)	(5.34)	(5.25)
BMDUM	0.70	0.71	0.67	0.63	0.71	0.68
	(4.64)	(4.58)	(4.32)	(3.63)	(4.71)	(4.61)
MOM	0.97	1.00	0.97	0.91	0.96	1.00
	(3.09)	(3.25)	(3.37)	(3.14)	(3.20)	(3.33)
MOMDUM	-0.24	-0.23	-0.16	-0.20	-0.26	-0.21
	(-1.53)	(-1.60)	(-1.04)	(-1.28)	(-1.67)	(-1.45)
DISP × Forecast Accuracy	**-1.11**	**-0.91**	**-1.13**	**-0.94**	**-1.03**	**-0.64**
	(-4.64)	**(-4.31)**	**(-3.94)**	**(-4.19)**	**(-4.28)**	**(-1.92)**
Forecast Accuracy	0.85	0.19	1.00	0.61	0.74	0.30
	(2.56)	(0.45)	(2.24)	(1.94)	(1.94)	(0.53)
DISP × CHAR		**-0.23**	**0.08**	**-0.15**	**-0.05**	**-0.56**
		(-1.04)	**(0.27)**	**(-0.69)**	**(-0.56)**	**(-1.16)**
CHAR		0.78	-0.31	0.32	0.14	0.94
		(2.03)	(-0.66)	(0.77)	(0.63)	(1.18)

Table 6 Continued

Panel B The dispersion-bias relation						
	Forecast Accuracy	*Information Environment*	*Stock Market Development*	*Investor Protection*	*Capital Openness*	*Intensity of Forecast Usage*
INTERCEPT	0.84	0.91	0.89	0.85	0.89	0.85
	(8.09)	(9.10)	(8.96)	(8.28)	(9.08)	(8.02)
DISP	-0.05	-0.05	-0.09	-0.05	-0.06	0.00
	(-1.26)	(-0.83)	(-1.76)	(-1.23)	(-1.08)	(0.00)
LOGMV	-0.06	-0.07	-0.06	-0.06	-0.06	-0.06
	(-8.52)	(-9.99)	(-8.80)	(-9.69)	(-10.25)	(-8.42)
LOGBM	0.01	0.01	0.00	0.01	0.00	0.01
	(0.37)	(0.43)	(0.25)	(0.50)	(0.15)	(0.43)
BMDUM	-0.07	-0.08	-0.08	-0.08	-0.08	-0.07
	(-1.45)	(-1.54)	(-1.58)	(-1.64)	(-1.48)	(-1.49)
MOM	-0.44	-0.43	-0.43	-0.43	-0.42	-0.44
	(-9.64)	(-10.01)	(-9.35)	(-9.62)	(-9.58)	(-9.55)
MOMDUM	0.20	0.25	0.21	0.21	0.23	0.21
	(10.46)	(10.48)	(11.52)	(10.80)	(11.29)	(10.46)
DISP × Forecast Accuracy	**0.32**	**0.31**	**0.27**	**0.26**	**0.30**	**0.49**
	(3.87)	**(3.67)**	**(3.33)**	**(2.99)**	**(3.49)**	**(4.25)**
Forecast Accuracy	-0.44	-0.25	-0.34	-0.32	-0.32	-0.40
	(-6.53)	(-4.44)	(-4.61)	(-4.32)	(-4.34)	(-5.00)
DISP × CHAR		**-0.01**	**0.11**	**0.06**	**0.04**	**-0.26**
		(-0.09)	**(1.74)**	**(2.61)**	**(0.46)**	**(-2.67)**
CHAR		-0.33	-0.19	-0.11	-0.23	-0.07
		(-6.96)	(-3.68)	(-3.67)	(-5.58)	(-1.09)

Table 7 1997−98 Asian financial crisis

Panel A reports the results of the following pooled regression on a sample of individual analysts' forecast revisions for stocks traded in Malaysia, Thailand and South Korea in 1996 (before the crisis) and 1999 (after the crisis): $Abret_i = \beta_0 + \beta_1 FREV_i + \beta_2 FREV_i \times TREAT_i + \beta_3 FREV_i \times POST_i + \beta_4 FREV_i \times POST_i \times TREAT_i + \beta_5 TREAT_i + \beta_6 POST_i + \beta_7 POST_i \times TREAT_i + \beta_k Control^k_i + \varepsilon_i$. *TREAT* is a dummy variable, which is equal to 1 if the forecast revision is for a Malaysian stock and 0 if it is for a stock from Thailand or South Korea. *POST* is equal to 1 if the forecast revision is issued in 1999 and 0 if it is issued in 1996. The set of control variables ($Control^k$) includes the stand alone control variables in estimating *ERC* as explained in Table 3, each of the control variable's interactions with *POST*, *TREAT* and *POST* × *TREAT*, and time fixed effect based on the forecast revision date.[26] Test statistics are based on standard errors clustered by both stock and analyst. Panels B and C report the results of the pooled regressions on a sample of mean reported forecasts for stocks traded in Malaysia, Thailand and South Korea in 1996 and 1999. The regression for Panel B is $ACCURACY_i = \beta_0 + \beta_1 TREAT_i + \beta_2 POST_i + \beta_3 POST_i \times TREAT_i + \beta_k Control^k_i + \varepsilon_i$. The dependent variable is the accuracy of monthly mean reported forecast. $Control^k$ includes firm size, book-to-market ratio, and momentum. The regression for Panel C is RET_i (or $BIAS_i$) = $\beta_0 + \beta_1 DISP_i + \beta_2 DISP_i \times TREAT_i + \beta_3 DISP_i \times POST_i + \beta_4 DISP_i \times POST_i \times TREAT_i + \beta_5 TREAT_i + \beta_6 POST_i + \beta_7 POST_i \times TREAT_i + \beta_k Control^k_i + \varepsilon_i$. The dependent variable is the stock return of the following month (*RET*) or the upward bias in the mean reported forecast (*BIAS*). The set of control variables in Panel C includes firm size, book-to-market ratio, momentum, and each characteristic's interactions with *POST*, *TREAT* and *POST* × *TREAT*. In Panels B and C, *POST* is based on the calendar year in which the mean forecast is reported, and test statistics are based on standard errors clustered by both stock and calendar month. For simplicity, we omit the coefficients on the control variables.

Panel A: Dependent variable =Average daily abnormal return around analysts' forecast revision		
	Estimate	*t-statistics*
FREV	-0.05	(-0.76)
FREV× TREAT	0.21	(2.39)
FREV× POST	0.07	(1.00)
FREV× TREAT × POST	**-0.20**	**(-1.94)**
TREAT	-0.23	(-1.23)
TREAT × POST	0.24	(0.83)

Panel B: Dependent variable = Monthly forecast accuracy		
	Estimate	*t-statistics*
TREAT	0.46	(4.27)
POST	0.09	(0.84)
TREAT × POST	**-0.32**	**(-2.69)**

Panel C: Dependent variable =	Monthly stock return		Monthly forecast bias	
	Estimate	*t-statistics*	*Estimate*	*t-statistics*
DISP	-0.18	(-1.15)	-0.12	(-3.17)
DISP × TREAT	-2.64	(-3.49)	0.72	(3.05)
DISP × POST	0.01	(0.02)	0.00	(0.11)
DISP × TREAT × POST	**3.16**	**(2.67)**	**-0.59**	**(-2.44)**
TREAT	-0.80	(-0.23)	0.89	(1.85)
POST	-9.76	(-2.08)	0.01	(0.03)
TREAT × POST	10.31	(1.48)	-0.06	(-0.10)

[26] Since we use the method of "demeaning" to control time fixed effect, the coefficient on *POST* is not available. The results are similar if time fixed effect is controlled in Panels B and C.

Online Appendix: Sample selection of non-U.S. stocks

This appendix explains the procedure we use to construct the non-U.S. sample.

Step 1: Retrieve summary statistics of analysts' earnings forecasts for international firms from the I/B/E/S summary file.

There are two types of summary files in I/B/E/S: an adjusted file (file name: *STATSUM_EPSINT* in WRDS) and an unadjusted file (file name: *STATSUMU_EPSINT* in WRDS). Following Diether et al. (2002), we rely on the summary statistics from the unadjusted file to calculate forecast dispersion in order to avoid the problems caused by I/B/E/S adjustment for stock splits. However, the unadjusted file does not include actual earnings-per-share (EPS), which is a variable needed to calculate forecast bias. Actual EPS (after adjustment for stock splits) is included in the adjusted file. Hence, we need to match the unadjusted summary forecast statistics with the adjusted actual EPS and make sure they are on the same scale with respect to stock splits. To achieve this, we follow the method in Glushkov (2009). Specifically, we merge the unadjusted file with the adjusted file to back out the split factor, with which we obtain the unadjusted actual EPS. In this matching process, it is important to ensure that the currency code of forecast statistics (*CURCODE* in I/B/E/S) is the same as the currency code of actual EPS (*CURR_ACT* in I/B/E/S). We focus on current fiscal-year annual EPS forecasts (i.e., *FPI* =1 in I/B/E/S). This process results in 2,469,933 firm-month observations with no missing unadjusted actual EPS whose forecast statistic dates (*STATPERS* in I/B/E/S) fall between January 1990 and November 2013 from the I/B/E/S universe. Our sample starts in January 1990 because Datastream begins to provide stock return data for a large number of international firms in 1990. Our sample ends in November 2013 because forecast statistics will later be matched with the following month's return, which ends in December 2013 (i.e., the last month of our return data).

Step 2: Match the I/B/E/S identifier *TICKER* with the Datastream identifier *DSCD*.

TICKER is the unique identifier for each firm in I/B/E/S, and *DSCD* is the unique six-digit identifier for each stock. Among the 2,469,933 firm-month observations retrieved in step 1, there are 34,415 unique *TICKERs*. We create a list based on the 34,415 *TICKERs* and then retrieve the corresponding *DSCD* for each *TICKER* from Datastream. Each of 34,415 *TICKERs* is matched with one unique *DSCD*. However, there is one case where one *DSCD* (= 14653D) is associated with two *TICKERs*. We manually check this case and choose the correct match. Therefore, we obtain 34,414 unique *TICKER-DSCD* matches. It's important to note that in this matching process, we search *DSCD* for *TICKER* because this process normally results in a firm's primarily listed stock. If we reverse this process (i.e., searching *TICKER* for *DSCD*), one *TICKER* is often matched with different *DSCD*s when a firm has several listings.

Step 3: Select stocks meeting our criteria.

The 34,414 stocks in step 2 are from 92 countries. Unless otherwise specified, we identify a stock's country based on the location of its primary exchange (*GEOLN* in Datastream). Among these

92 countries, many countries will not have enough observations to calculate a reliable dispersion effect, especially countries that began to have records on I/B/E/S only recently. In order to reduce our data collection effort, we delete those countries for which I/B/E/S begins to provide forecasts after year 1995, which results in 47 countries and 31,415 stocks. As in Chui et al. (2010), we include only stocks traded on the primary stock exchanges in each country, which results in 31,188 stocks. Furthermore, we include only primary listings (i.e., requiring Primary = 'P' in Datastream and excluding those stocks with missing information on primary listing status), which results in 28,421 stocks.

Step 4: Retrieve monthly stock return from Datastream.

We match our refined sample of 28,421 stocks in step 2 with the forecast sample in step 1, which results in 2,196,359 stock-month observations. These observations are merged with the stock returns of the following month. We calculate monthly stock return using monthly return index (*RI* in Datastream) denominated in U.S. dollars. One issue with the return index in Datastream is that after a stock is delisted, the return indexes after delisting are copied for later periods, which results in a trailing of zero returns. Following Ince and Porter (2006), we delete all monthly return observations from the end of the sample period to the first nonzero return.[1] Only 1.5% of the above 2,196,359 firm-month observations have missing returns in the following month.

Step 5: Delete observations with missing variables and potential data errors.

We delete observations with missing forecast dispersion, which is defined as the ratio of the standard deviation of analysts' current fiscal-year annual earnings-per-share forecasts (i.e., forecasts of forthcoming earnings-per-share) to the absolute value of the mean forecast. This results in 1,628,098 stock-month observations. We then delete 368 observations with missing market capitalization (*MV* in Datastream). We also delete 1,350 observations whose earnings announcement date (*ANNDATS_ACT* in I/B/E/S) is prior to the fiscal year end (*FPEDATS* in I/B/E/S), 12,207 observations whose forecast statistic date (*STATPERS* in I/B/E/S) is later than the earnings announcement date, and 33,256 observations whose forecast statistic date is more than 12 months prior to the earnings announcement date. These observations are likely to be data errors. These criteria result in 1,580,917 stock-month observations. Next, we delete observations with holding period returns at the top and bottom 1% within each country, as many of these extreme returns are likely to be the result of coding error (McLean et al. 2009). We also delete observations with forecast error, calculated as the absolute value of the difference between monthly consensus forecast and actual

[1] Another method adopted in the literature to address this issue is to delete returns with non-positive trading volumes. We find that for some countries (e.g., Germany), Datastream begins to have records on trading volume later than it begins to have records on return index. This means that using the method of deleting returns with non-positive trading volumes will result in the deletion of many valid return observations. Hence, we do not use this method.

earnings-per-share scaled by the latter, at the top 99% within each country[2], because these forecasts are likely to be the results of data errors. This results in 1,533,909 stock-month observations.

Step 6: Select countries with sufficient observations.

For each month we limit our sample to countries with at least 100 observations. We also delete countries with a return history of fewer than 60 months over our sample period, which runs from February 1990 to December 2013. This results in 1,241,339 stock-month observations from 23 non-U.S. countries.

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[2] The lower bound of forecast error is 0.