Global Expertise of Financial Analysts

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Abstract

We describe the challenges of forecasting earnings in a globally interconnected marketplace, and we document inefficient use of information regarding foreign country exposures and expected country GDP growth at the consensus and individual forecast levels. A country's proximity to the US, importance to the firm, and visibility, as well as availability of more precise information about foreign country exposures, contribute to consensus forecast efficiency. We identify a dimension of individual analyst global expertise—similarity in exposure between the firm and the rest of the firms in the analyst portfolio—and show that it contributes to forecast efficiency, accuracy, and informativeness and that it helps the analyst achieve the coveted all-star rank, suggesting that globalization not only poses a challenge but also creates an opportunity for research providers and analysts to distinguish themselves.

Keywords: financial analysts; earnings forecasts; global expertise
JEL Classification: G10, G17, M41

"(I)t is no longer enough for analysts covering stocks in developed economies to focus on their local economy, or even on developed economies. For example, for many US companies a growing share of their business is likely to come from the developing world. So to do your job today as a US analyst, it is important to understand what is going on in these developing countries and to be able to identify which US companies are likely to be able to compete effectively in these markets." (Healy [2014], p.15)

1. Introduction

The task of forecasting corporate earnings in a global world is truly challenging. An accurate forecast must incorporate information about all foreign economies that a company is exposed to as well as the rates at which these economies grow. This challenge is further compounded by the fact that companies continuously adjust their foreign activities and that foreign economies grow at different rates at different times. In this study, we examine whether sell-side equity analysts rise to the challenge of forecasting earnings in a global world.

Equity analyst forecasts are generally superior to statistical forecasts (e.g., Bradshaw, Drake, Myers and Myers [2012], Brown and Rozeff [1978]) and are informative to investors (Lys and Sohn [1990]); at the same time, they are inefficient and biased (Abarbanell and Bernard [1992], DeBondt and Thaler [1985]). Prior evidence of forecast inefficiency raises the possibility that analysts may fail to fully rise to the challenge of forecasting earnings in a global world. It is important to understand, within a global setting, the degree of analyst forecast (in)efficiency, its variation, and the consequences for investors and analysts themselves. These issues are more pertinent now than ever because companies operate in an increasingly global world. For example, in 2014, 34% of all publicly listed US companies reported foreign sales that, on average, accounted for 40% of their total sales (see Figure 1 for indicators of the rising significance of US companies' foreign operations over time).

To shed light on analyst global expertise, we address three questions. At the *consensus* forecast level, what country-level factors determine whether information about foreign country exposures and expected performance is used efficiently? At the *individual analyst* level, what analyst and broker-level factors determine whether this information is used efficiently? What are the capital market and labor market consequences of inefficient information use?

We measure a company's foreign country exposure as the ratio of foreign country sales to total sales, extracted from the Compustat Segment file (Li, Richardson and Tuna [2014]). The sum product of foreign country exposures and one-year-ahead International Monetary Fund's (IMF) country GDP growth forecasts yields a simple but admittedly noisy summary measure of what an analyst must know to forecast earnings in a global world. We refer to this measure as *MACRO_F*.

To maximize the power of our tests, we focus on firms with substantial foreign sales that are more than 25% of total sales. From 1998 to 2014, the number of these companies increased from 607 to 970, and the percentage of their foreign sales increased from 42% to 55%. The importance of these firms for the health of the US stock market and economy has become immense: in 2014, these companies accounted for 40% of the total US market capitalization.

Analyzing one-year-ahead consensus EPS forecasts, we find evidence that analysts underreact to information about foreign country exposures and expected country performance. A one standard deviation increase in *MACRO_F* corresponds to an approximately 0.25 percent increase in the consensus forecast error, which is approximately 27% of the mean consensus forecast error. Furthermore, we document systematic patterns in information use. Specifically, the consensus forecast is more efficient at impounding information about countries that are geographically closer to the US, that account for a larger share of the company's sales, and that have higher analyst following. We conclude that a country's geographic proximity to the US, its economic importance to the firm, and its visibility facilitate efficient information use, consistent with theories of limited attention and information processing cost (Sims [2003], Hirshleifer and Teoh [2003]). Finally, the consensus forecast is more efficient when a firm discloses foreign sales at the country level than at the regional level, consistent with the idea that having more precise information about foreign sales facilitates the task of forecasting earnings.

Turning to individual analyst-level analysis, we expect that individual analysts' use of information about country exposures and expected country growth in forecasting company *j*'s earnings, which we refer to as analyst global expertise, likely depends on the similarity between company *j*'s country exposures and the country exposures of the rest of the companies in the analyst's portfolio. Intuitively, an analyst's ability to solve the forecasting problem posed by firm *j* would be enhanced if the rest of the firms pose similar forecasting problems because of economies of scale in the acquisition and production of information.

Empirically, we start by measuring pairwise distances in foreign country exposures (sales in foreign country divided by total firm sales) between firm *j* and the other firms in the analyst's portfolio. The weighted average (by the other firms' market values) of all these distances multiplied by −1, which we label *SIMEXP_F*, captures the notion of the similarity between firm *j*'s foreign country exposures and those of the other firms in the analyst's portfolio. (For a numerical example of the calculations, see Appendix II.) We expect *SIMEXP_F* to encapsulate an important dimension of analysts' global expertise and to be associated with a more efficient use of global information because a greater similarity in foreign exposures among covered stocks allows an analyst to take advantage of greater economies of scale in information gathering and production and to make more efficient resource allocation decisions. We note that our tests include as controls various firm, broker and analyst characteristics. In particular, we include analysts' country-level and industry-level concentrations (Herfindahl Index measures). Therefore, our *SIMEXP_F* variable captures a dimension of analyst global specialization and expertise that is distinct from the country and industry concentration measures seen in prior literature (e.g., Sonney [2009]).

To investigate whether *SIMEXP_F* facilitates the efficient impounding of global information in analyst forecasts, we run regressions of individual analyst forecast errors on *MACRO_F* and its interactions with *SIMEXP_F*. A negative coefficient of the interaction term *MACRO_F*×*SIMEXP_F* suggests that similarity within an analyst's portfolio regarding firms' foreign exposures helps mitigate the inefficiency in incorporating *MACRO_F* in analyst forecasts. We find results consistent with our prediction: analyst inefficiency in using information about a firm's country exposure and expected country performance, *MACRO_F*, is decreasing with the similarity in firm foreign exposures within the analyst's portfolio. A one standard deviation increase in *SIMEXP_F* from the sample mean reduces the inefficiency in *MACRO_F* by 35%, which is statistically and economically significant.

Viewing *SIMEXP_F* as a measure of analyst global expertise, we explore whether analyst global expertise is positively related to forecast accuracy and price impact. A positive relation cannot be presumed based on our earlier result that analysts with greater *SIMEXP_F* make more efficient use of foreign exposures and foreign country expected growth information. To the extent that analysts make tradeoffs among different tasks when allocating resources, an analyst who efficiently uses one type of information may inefficiently use another.[1]

Our results indicate that analysts with higher global expertise as measured by *SIMEXP_F* indeed issue forecasts with higher accuracy and higher price impact. A one standard deviation

[1] For example, Luo and Nagarajan [2015] show that supplier chain analysts make superior forecasts for supplier firms but low-quality forecasts for other firms in their portfolios.

increase in *SIMEXP_F* relative to her peers will increase her relative accuracy by 1.2%. In comparison, a one standard deviation increase in an analyst's experience will increase her relative accuracy by 1.4%. Furthermore, a one standard deviation increase in *SIMEXP_F* increases the market response to forecast news by approximately 11%. In comparison, the analyst's experience does not significantly increase the market response to forecast news.

Finally, we explore whether analyst global expertise as measured by *SIMEXP_F* is positively associated with the likelihood of an analyst being ranked as an all-star in the Institutional Investor Magazine's annual poll. All-star ranking is a widely accepted measure of analyst reputation and a determinant of analyst compensation even after controlling for other important performance metrics (Groysberg, Healy and Maber [2011]), making it an effective proxy for analyst incentives. Here we find that an analyst with higher *SIMEXP_F* is more likely to be ranked as an all-star and less likely to lose her all-star ranking. A one standard deviation increase in *SIMEXP_F* from the sample mean increases the probability of being ranked as an all-star by 0.5 percent and decreases the probability of losing all-star ranking by 3.3 percent. Note that the corresponding sample probabilities are 11.2 percent and 27.3 percent, respectively. This means that a one standard deviation increase in global expertise results in 5% and 12% changes in the respective probabilities of being an all-star and losing the all-star position, which are economically significant.

In supplemental analyses, we show that our results are robust to alternative constructs of the similarity measure. Alternatively, we view all firms an analyst covers as a single (hypothetical) firm, and we aggregate sales in each country from these firms. We then calculate its similarity with firm *j*. All our results are retained with this alternative measure. Finally, we conduct our analyses for the subsample of initially covered firms and our inferences remain the same.

A vast body of literature in accounting and finance examines the properties and consequences of analyst forecasts but largely overlooks the increasingly interconnected global nature of today's product and financial markets (see recent surveys by Kothari, So and Verdi [2016] and Beyer, Cohen, Lys and Walther [2010]). We contribute to this literature by describing the challenges of forecasting earnings in a globally interconnected marketplace, assessing the extent to which analysts accomplish this task, identifying factors that determine analyst global expertise, and showing that the latter is rewarded by the labor market.

Our study fits well with the nascent literature on how globalization affects market price efficiency (e.g., Claus and Thomas [2001], Li *et al.* [2014], Albuquerque, Ramadorai and Watugala [2015], Huang [2015]). The emerging consensus in this literature is that the market is inefficient with respect to information that concerns various aspects of a firm's global activities and exposures. Our results that equity analyst forecasts are inefficient with respect to information about foreign country exposures and expected country growth forecasts naturally complement the Li *et al.* [2014] finding that the market is inefficient with respect to this information. Importantly, we extend this literature by focusing on how analyst global expertise can help mitigate the inefficient use of global information.

While a number of prior studies have examined analyst research in a global setting (see Section 2 for a summary), they answer different research questions and rely on different test designs. For example, Khurana, Pereira and Raman [2003] and Duru and Reeb [2002] show that analysts are less efficient in impounding information about US firms' foreign (as opposed to domestic) operations. While these studies make no distinction among the sources of a firm's foreign exposures, we show that analyst global expertise is highly context-specific, as it varies with the characteristics of each foreign country (e.g., its geographic proximity to the US, its visibility and its significance to a firm's overall operations) and with the commonality within an analyst's research portfolio in terms of geographic exposure. Our analyses illustrate that the issue of analyst forecast efficiency in the global setting is highly nuanced and more textured than previously entertained in the literature.

Our results should be interpreted with the following caveats in mind. First, we focus on firms incorporated in the US and their foreign exposures. While the basis of our predictions may apply to multinational firms in general, we caution that our inferences may not extend to firms incorporated outside of the US. Second, we quantify the information germane to an analyst's understanding and forecast of a firm's foreign operations through two vectors: i) the ratio of foreign country sales to total sales to reflect a firm's foreign country exposures and ii) country GDP growth forecasts. Even though this information structure (following Li *et al.* [2014]) is simple to implement and intuitive to understand, it is not designed to capture all information dimensions pertaining to a firm's foreign operations. Furthermore, the sales-ratio-based (GDP-based) measure likely captures foreign exposure (country growth) with error.

The rest of the paper proceeds as follows. Section 2 summarizes related research. Section 3 discusses the framework of predicting earnings using firms' country exposures and GDP growth forecasts, and it replicates Li *et al.* [2014]. Section 4 explores whether consensus forecasts fully incorporate such information and factors that affect the efficient use of information. Section 5 explores broker and analyst factors that facilitate the use of macro information at the individual analyst level and examines the consequences of analyst global expertise in the stock market and labor market. Section 6 concludes.

2. Related Studies on Analyst Research in the Global Setting

Several earlier studies document that analysts forecast the foreign earnings component of

US firms inefficiently. Specifically, Khurana *et al.* [2003] show that analysts underestimate the persistence of US firms' foreign earnings. Duru and Reeb [2002] find that analyst forecasts exhibit lower accuracy and higher optimism for US firms with greater international operations. These studies combine a firm's foreign operations, treating them as a single, homogenous component and not distinguishing among the firm's exposures to different parts of the world. Our analysis, on the other hand, recognizes the complexity of an analyst's task, differentiating the various sources of a firm's foreign earnings and accounting for economic growth heterogeneity. It tackles issues shown in prior work to bear on the efficiency of security prices (Li *et al.* [2014]).

Our paper is related to a number of prior studies that examine analyst research in the international setting. Kini, Mian, Rebello and Venkateswaran [2009] and Sonney [2009] study the relation between forecast accuracy and analyst country (and industry) specialization, but they report conflicting results.[2] Both studies analyze samples of international firms, where a firm is identified with a single home country based on its headquarters location. Our research setting is fundamentally different. We focus on US firms, but our analysis recognizes the fact that many of these firms are global in nature and that the headquarters location is inadequate in defining these firms geographically. Despite these differences, we construct and include as controls country and industry concentration measures (based on the Herfindahl Index and analogous to those in Sonney [2009]). The results on our main variable of analyst global expertise (*SIMEXP_F*) remain robust, suggesting that our measure captures a distinct aspect of analyst specialization and expertise from the country and industry concentration measures in prior literature.

[2] Sonney [2009] constructs country and industry concentration measures based on the Herfindahl Index to gauge analyst specialization and find a *positive* relation between analyst forecast accuracy and their *country specialization* for a sample of European firms. Kini *et al.* [2009] use a simple count of the number of countries (industries) covered by an analyst to measure his/her country (industry) diversification and find a *positive* relation between analyst forecast accuracy and their *country diversification* for firms in more than 50 countries, including the US.

Finally, our study is related to Malloy [2005] and Bae, Stulz and Tan [2008], who show that analyst proximity to a firm's headquarters in the US (Malloy [2005]) and internationally (Bae *et al.* [2008]) enhances forecast accuracy. While our focus is on US firms with global operations, our findings that a country's proximity to the US facilitates forecast efficiency and accuracy are consistent with the idea that geographic distance matters.

3. Forecasting Earnings of a Global Company

3.1. Globalization trend

Figure 1 explores the trend toward globalization for US firms in the period from 1998 to 2014 (see Table 1 for details about the sample). The percentage of firms with non-zero foreign sales and significant (25% or more) foreign sales steadily increased from 17% and 8% in 1998 to 34% and 24% in 2014, respectively. The percentage of foreign sales for firms that report non-zero foreign sales also increased from 27% in 1998 to 40% in 2014. The economic importance of firms with substantial foreign sales in the US capital market cannot be overstated. In 2014, these firms accounted for 40% of the total US market capitalization.

3.2. Earnings forecasting framework

A global company has exposures to multiple economies (we use economy and country interchangeably). Our measurement approach exploits geographic segment sales disclosures made by US firms and available in the Compustat Annual Fundamental Historical Segments dataset for the period 1998–2014.[3] Firms report sales at the country (e.g., US) or at the regional (e.g., North America) level. We use country level disclosures when available. When absent, we allocate

[3] SFAS No. 131 (effective 1997) changes the way a segment is defined and reported compared to the previous rules under SFAS 14. To ensure comparability and consistency in geographic segment data, we focus on the post-SFAS 131 period.

regional sales to country sales using a GDP-based weighting scheme, which allocates more sales to economically more important countries (Roberts [1989], Li *et al.* [2014]). We assume that firm j's exposure to country n in year $t-1$ can be measured by the firm's country sales, scaled by total sales, $s^n_{j,t-1}$. We denote the vector of firm j's country exposures with $S_{j,t-1} = (s^1_{j,t-1}, s^2_{j,t-1}, \cdots, s^N_{j,t-1})$.

Our empirical approach to measuring country exposures is prone to measurement error. We do not consider how other components of income may depend on country performance, and there is much subjectivity both in firm reporting of geographic sales and in allocating geographic sales to countries. According to Balakrishnan, Harris and Sen [1990], however, the allocation of geographic sales to country sales is reasonably close to the actual country-level sales.

Prior studies document that firm performance is associated with macroeconomic condition variables (Li, Vassalou and Xing [2006], Vassalou [2003]). As a summary indicator of macroeconomic conditions, real GDP growth forecasts are useful in predicting firm performance (Li *et al.* [2014]). We obtain country-level annual real GDP (in US dollars) and GDP growth forecasts from the International Monetary Fund (IMF) World Economic Outlook database.[4] Prior studies have shown that IMF GDP growth forecasts are accurate and rational (Ashiya [2006], Tsuchiya [2013]). GDP growth forecasts for calendar years t and t+1 are published in April and September of year t. We create a GDP growth forecast for firm j country n in fiscal year t, g^n_t, using the latest IMF forecasts[5]. We denote the vector of GDP growth forecasts with

[4] The data are publicly available at IMF's website: http://www.imf.org/external/pubs/ft/weo/2016/01/weodata/index.aspx.

[5] If a firm's fiscal year end is different from December, we combine the one-year-ahead and two-year-ahead IMF forecasts to create g^n_t. For example, if firm j's fiscal year ends in March, then $g^n_{jt} = 9/12 \times f^n_t + 3/12 \times f^n_{t+1}$, where f^n_t and f^n_{t+1} are the latest IMF GDP growth forecasts for country n in calendar years t and $t+1$.

$G_{jt} = (g_{jt}^1, g_{jt}^2, \cdots, g_{jt}^N)$. Finally, we assume that the dot product of firm *j*'s country exposure vector, $S_{j,t-1}$, and country GDP growth forecast vector, G_{jt}, i.e., $S_{j,t-1} \cdot G_{jt} = \sum_{n=1}^{N} s_{j,t-1}^n \times g_{jt}^n$, which we call *MACRO*, summarizes what an analyst must know to forecast the earnings of global firm *j*. We further decompose *MACRO* into its domestic, *MACRO_D*, and foreign, *MACRO_F*, components to assess whether the predictive ability comes from the foreign component. That is, $MACRO\_D_{jt}$ = $s_{j,t-1}^{US} \times g_{jt}^{US}$, and $MACRO\_F_{jt}$ = $\sum_{n \neq US}^{N} s_{j,t-1}^n \times g_{jt}^n$.

Li *et al.* [2014] demonstrate that *MACRO* and *MACRO_F*, in particular, are useful in forecasting earnings, but given the differences in sample composition and research designs, we seek to validate this assumption below.

3.3. Predicting future earnings with MACRO

At the beginning of each year *t*, we predict firm *j*'s year *t* earnings, calculated as actual earnings per share (EPS) in year *t* scaled by stock price at the beginning of year *t*, A_{jt}, as a function of $MACRO_{jt}$ or its components $MACRO\_F_{jt}$ and $MACRO\_D_{jt}$:

$$A_{jt} = \alpha + \beta MACRO_{jt} + \text{Firm Controls} + \varepsilon_{jt} \tag{1}$$

$$A_{jt} = \alpha + \beta_1 MACRO\_F_{jt} + \beta_2 MACRO\_D_{jt} + \text{Firm Controls} + \varepsilon_{jt} \tag{2}$$

We also control for other firm characteristics, including firm *j*'s actual EPS in year $t-1$ scaled by stock price at the beginning of year $t-1$, $A_{j,t-1}$; firm *j*'s market capitalization at the end of year $t-1$, $LogMV_{j,t-1}$; firm *j*'s book-to-market ratio at the end of year $t-1$, $BTM_{j,t-1}$; an indicator for negative earnings before extraordinary items for firm *j* in year $t-1$, $LOSS_{j,t-1}$; an indicator of firm *j* paying dividends in year $t-1$, $D\_DIV_{j,t-1}$; and firm *j*'s dividend yield in year $t-1$, $DY_{j,t-1}$; as well as industry and year fixed effects. See Appendix I for detailed variable definitions.

We estimate equations (1) and (2) on a sample of 9,843 firm-year observations. A key sample requirement imposed to increase power is that foreign sales be 25% or more of total sales. See Table 1 for more information about the sample and the steps taken to derive it.

Table 2 panel A reports sample statistics. The average firm has earnings of 3.752% of its stock price, a market capitalization of $7.5 billion, a 0.494 book-to-market ratio, and 62.5% of institutional ownership, suggesting the sample mainly consists of large firms. The variable of interest, $MACRO_{jt}$, has a mean (median) of 2.462% (2.692%) with a standard deviation of 1.653%, and its foreign and domestic components, $MACRO\_F_{jt}$ and $MACRO\_D_{jt}$, have means (medians) of 1.358% (1.231%) and 1.119% (1.178%) with standard deviations of 1.228% and 1.009% respectively. Note that these numbers differ from Li *et al.* [2014] because their sample includes firms from 45 countries over the 1998–2010 period, while ours covers only US firms for the period 1998–2014.

Table 3 columns (1) and (2) report the OLS estimation results of equations (1) and (2). We find that the coefficient on our variable of interest, $MACRO_{jt}$, is positive at 0.347 and significant at the 1% level, suggesting that a one standard deviation increase in $MACRO_{jt}$ predicts an increase of 0.57 percent in future earnings, which translates to a 15.3% increase from the sample mean. When we decompose $MACRO_{jt}$ into domestic and foreign components, we find that the coefficient on the foreign component, $MACRO\_F_{jt}$, is 0.383, significant at the 1% level, while the coefficient of the domestic component, $MACRO\_D_{jt}$, is positive but insignificant. $MACRO\_F_{jt}$ is also economically more significant. A one standard deviation increase in $MACRO\_F_{jt}$ predicts an increase of 0.47 percent in future earnings, which translates to a 12.5% increase from the sample mean.

In columns (3) and (4), we examine whether our results are robust to controlling for the analyst consensus, $Cons_{jt,}$, defined as the first consensus forecast for firm j in year t after year $t-1$'s earnings announcement, scaled by stock price at the beginning of year t. The consensus forecast loads significantly and positively, with a coefficient of approximately 0.42, and it is significant at the 1% level. While the magnitudes of the coefficients of $MACRO_{jt}$ and $MACRO\_F_{jt}$ are reduced to 0.212 and 0.230, respectively, they remain significant at the 1% level, suggesting that $MACRO_{jt}$ and $MACRO\_F_{jt}$ are not subsumed by the analyst consensus. We note that the result regarding $Cons_{jt}$ is consistent with that of prior studies with US firms (Givoly and Lakonishok [1979]) but is different from Li *et al.* [2014], where the consensus forecast is insignificant in predicting return on assets, presumably due to sample composition, e.g., our sample includes only US firms over the period 1998–2014, whereas theirs includes international firms over the period 1998–2010.

The coefficients on the control variables are generally consistent with the findings of Li *et al.* [2014]. Specifically, lagged actual earnings, A_{jt-1}, size, $LogMV_{jt-1}$, and the dividend paying indicator, D_DIV_{jt-1}, load positively and significantly, while book-to-market ratio, BTM_{jt-1}, $LOSS_{jt-1}$, and dividend yield, DY_{jt-1}, load negatively and significantly.

4. Consensus Forecast Analysis

We examine two questions: 1) whether analyst consensus forecasts fully incorporate information about country exposures and expected country GDP growth and 2) what factors influence efficient information use. To address the first question, we regress consensus forecast errors, CFE_{jt}, on $MACRO_{jt}$ or $MACRO\_F_{jt}$ and test for a non-zero slope coefficient; we expect a higher slope coefficient on $MACRO\_F_{jt}$, which considers only foreign countries:

$$CFE_{jt} = \alpha + \beta_1 MACRO\_F_{jt} + \beta_2 MACRO\_D_{jt} + \text{Firm Controls} + \varepsilon_{jt} \quad (3)$$

To address the second question, we first sort countries into two groups based on a country's economic importance to the firm, proximity to the US, and visibility. We calculate $MACRO\_F_{jt}$ for each group and test for coefficient equality across the two groups. Second, we separate firm-reported countries from regions and calculate $MACRO\_F_{jt}$ for each group. Third, we sort firms into two groups based on their total foreign exposure, calculate $MACRO\_F_{jt}$ for each group, and test for coefficient equality across the two groups:

$$\begin{aligned} CFE_{jt} &= \alpha + \gamma_1 MACRO\_F\_HighGroup_{jt} + \gamma_2 MACRO\_F\_LowGroup_{jt} \\ &\quad + \beta_2 MACRO\_D_{jt} + \text{Firm Controls} + \varepsilon_{jt} \end{aligned} \tag{4}$$

The motivations for this sorting as well as details on the research design are provided below.

4.1. Factors that influence efficient information use

Assuming limited attention and information processing resources, forecasting performance should be improved by shifting attention and resources away from countries to which the firm has minimal exposures to countries to which the firm has large exposures. We construct $MACRO\_F\_Top5_{jt}$, which considers only the top five countries with the largest shares of firm total sales, and $MACRO\_F\_NonTop5_{jt}$, which excludes these five countries; we expect more efficient use of $MACRO\_F\_Top5_{jt}$ than $MACRO\_F\_NonTop5_{jt}$.

There is evidence to suggest that forecast accuracy is inversely related to geographic distance (Malloy [2005], Bae *et al.* [2008]). We construct $MACRO\_F\_Close5_{jt}$, which focuses on the five countries whose capital cities are closest to Washington DC, and its complement $MACRO\_F\_NonClose5_{jt}$; we expect more efficient use of $MACRO\_F\_Close5_{jt}$ than $MACRO\_F\_NonClose5_{jt}$.

Analyst coverage is an often-used measure of information availability and visibility at the firm level. Furthermore, many market anomalies are weaker for companies with greater analyst coverage (Brennan and Hughes [1991], Hong, Kubik and Solomon [2000], Gleason and Lee [2003]), consistent with a positive relation between analyst coverage and information use. Building on this line of research, we construct a measure of analyst coverage of a country by summing over analyst coverage of US firms with non-zero exposures to the respective country and $MACRO\_F\_Cov5_{jt}$, which considers the five countries with highest analyst coverage, and its complement, $MACRO\_F\_NonCov5_{jt}$. We predict more efficient use of $MACRO\_F\_Cov5_{jt}$ than $MACRO\_F\_NonCov5_{jt}$.

Forecasts should be more efficient when information about foreign sales is more precise: that is, when a firm reports foreign sales at the country level as opposed to at the regional level. We construct $MACRO\_F\_Cntry_{jt}$ using country level disclosures and $MACRO\_F\_Reg_{jt}$ using regional level disclosures, and test whether analysts use $MACRO\_F\_Cntry_{jt}$ more efficiently than $MACRO\_F\_Reg_{jt}$.

As a firm's overall foreign exposure increases, the importance of accurately assessing foreign country growth rates and a firm's exposures also increases. Analysts will accordingly allocate more of their efforts and resources to firms with higher overall foreign exposure. We therefore sort firms into quartiles each year based on their overall foreign exposure. Denoting membership in the top quartile (remaining quartiles) with $MACRO\_F\_HiXps_{jt}$ ($MACRO\_F\_LoXps_{jt}$), we predict more efficient use of $MACRO\_F\_HiXps_{jt}$ than $MACRO\_F\_LoXps_{jt}$.

4.2. Results

We define consensus forecast errors, CFE_{jt}, as actual EPS minus analysts' consensus forecast EPS, scaled by stock price at the beginning of year *t*, then multiplied by 100 (in percentage), i.e., $A_{jt} - Cons_{jt}$. Control variables include lagged earnings (DeBondt and Thaler

[1985]), $A_{j,t-1}$; annual size-adjusted abnormal returns (Abarbanell [1991]), $ANNRET_{j,t-1}$; accruals (Bradshaw, Richardson and Sloan [2001]), $ACCRUAL_{j,t-1}$; size (Doukas, Kim and Pantzalis [2002]), $LogMV_{j,t-1}$; institutional ownership (O'Brien and Bhushan [1990]), $IOR_{j,t-1}$, book-to-market (Doukas *et al.* [2002]), $BTM_{j,t-1}$; loss (Duru and Reeb [2002]), $LOSS_{j,t-1}$; standard deviation of ROA (Duru and Reeb [2002]), $STDROA_{j,t-1}$; financial leverage (Hutton, Lee and Shu [2012]), $LEV_{j,t-1}$; and the cross-sectional dispersion of GDP growth forecasts, $GDPDISP_{jt}$.

Table 2 panel A reports descriptive statistics for the sample used in this section. The mean (median) consensus forecast error is −0.914% (−0.019%), with a standard deviation of 4.824%. The means (medians) of $MACRO\_F\_Top5_{jt}$ and $MACRO\_F\_NonTop5_{jt}$ are 0.803% (0.557%) and 0.557% (0.550%), respectively, suggesting that the top five countries with the largest sales shares contribute significantly to $MACRO\_F_{jt}$.

Table 4 columns (1) and (2) report results from our test of equation (3)—whether the consensus incorporates information about $MACRO_{jt}$ and its components. The coefficient on $MACRO_{jt}$ in column (1) is 0.169, significant at the 10% level, suggesting that analysts, on average, underreact to $MACRO_{jt}$ information. In column (2), the coefficient on $MACRO\_F_{jt}$ is positive at 0.202 and significant at the 5% level, while the coefficient of the domestic component, $MACRO\_D_{jt}$, is positive but insignificant. A one standard deviation increase in $MACRO\_F_{jt}$ increases consensus forecast error by 0.25 percent, which translates to a 27% increase from the mean consensus forecast error. The coefficient of $MACRO\_F_{jt}$ is larger than that of $MACRO_{jt}$ and $MACRO\_D_{jt}$, but the difference is not statistically significant.

Table 4 columns (3) to (7) report the estimation results of equation (4)—what factors influence efficient use of information about country exposures and expected country GDP growth forecasts. The coefficient on $MACRO\_F\_NonTop5_{jt}$ is positive, 0.530, and significant at the 1%

level, while the coefficient of $MACRO\_F\_Top5_{jt}$ is insignificant. The difference between the two coefficients is significant at the 5% level. A one standard deviation increase in $MACRO\_F\_NonTop_{jt}5$ corresponds to a 0.61 percent increase in consensus forecast error, which translates to a 66.4% increase from its sample mean. Similar patterns exist for the pairs $MACRO\_F\_Close5_{jt}$ and $MACRO\_F\_NonClose5_{jt}$, $MACRO\_F\_Cov5_{jt}$ and $MACRO\_F\_NonCov5_{jt}$, and $MACRO\_F\_Cntry_{jt}$ and $MACRO\_F\_Reg_{jt}$, except that the coefficient of $MACRO\_F\_Cov5_{jt}$ is not significantly different from that of $MACRO\_F\_NonCov5_{jt}$. The coefficients of $MACRO\_F\_HiXps_{jt}$ and $MACRO\_F\_LoXps_{jt}$ are 0.209 and 0.393, significant at the 5% and 10% levels, respectively, suggesting the inefficiency exists both for firms with high and low foreign exposure. The difference between the two coefficients is statistically significant at the 5% level, which implies smaller forecast inefficiency when the firm has greater overall foreign exposure.

To sum up, the evidence in Table 4 suggests that analysts do not efficiently use information about country exposures and GDP growth forecasts and such inefficiency is reduced for countries that are more important, geographically closer to the US, and more visible, for firms whose overall foreign exposure is higher, and when the information about exposure is more precise, consistent with the implications of theories of limited attention and information processing resources (e.g., Corwin and Coughenour [2008], Hirshleifer and Teoh [2003], Sims [2003]).

5. Individual Analyst Forecast Analysis

5.1. Are individual forecasts efficient with respect to MACRO?

In this section, we explore what broker and analyst factors facilitate the use of *MACRO* at the individual level. Knowledge of how the use of *MACRO* varies as a function of observable broker and analyst characteristics should be helpful to investors in adjusting for forecast deficiencies and to analysts and research directors in organizing analyst research portfolios.

A unique feature of the task of covering global firms is that an analyst must estimate country exposures for each firm in her portfolio. Suppose an analyst follows three firms, A, B, and C, each generating earnings in three countries. If these firms have no overlapping country exposures, then the analyst would have to estimate nine country exposures. If these firms have exposures to the same three countries, and furthermore, if these exposures are the same (or approximately the same), the analyst would have to estimate only three country exposures. Intuitively, the task magnitude is greatly reduced when the analyst must solve the same problem three times compared to when she must solve three different problems at once. The reduction in task magnitude can also be framed as economy of scale benefits: the quantity of information useful in assessing a firm's exposure triples when firms A, B, and C have the same country exposures.

We calculate similarity in exposure between firm *j* and all other firms in analyst *i*'s portfolio in year *t*, $SIMEXP_{ijt}$, in two steps. We first calculate the distance in exposures between firm *j* and firm *k* as $DIST_{j,k,t} = \sqrt{\sum_{n=1}^{N}(s_{j,t}^{n} - s_{k,t}^{n})^2}$. Then, we calculate the value-weighted average of $DIST_{j,k,t,}$, with the weights given by firm *k*'s market value divided by the collective market value, multiplied by −1.[6] By construction, $0 \geq SIMEXP_{ijt} \geq -\sqrt{2}$. We expect more efficient use of *MACRO* when *SIMEXP* is higher.

We decompose *SIMEXP* into similarity in domestic exposure, *SIMEXP_D*, and similarity in foreign exposure, *SIMEXP_F*, just like we decompose *MACRO* into *MACRO_D* and

[6] We assume that more attention and resources are devoted to firms with greater market value. If firm B has larger market capitalization than firm C, we posit greater economy of scales benefits when firm A's exposure is more like firm B's exposure (as opposed to a simple average of B's and C's exposures). Alternatively, we use the equal-weighted average of $DIST_{jkt}$ multiplied by −1; our results are slightly weaker but qualitatively similar.

MACRO_F. Specifically, we first calculate the distance in domestic exposures and foreign exposures between firm *j* and firm *k* in analyst *i*'s portfolio in year *t* as $DIST^{D}_{j,k,t} = \left| s^{US}_{j,t} - s^{US}_{k,t} \right|$ and $DIST^{F}_{j,k,t} = \sqrt{\sum_{n \neq US}^{N} (s^{n}_{j,t} - s^{n}_{k,t})^2}$, respectively. We then calculate the market-value-weighted average of $DIST^{D}_{j,k,t}$ and $DIST^{F}_{j,k,t}$, multiplied by −1.

We also explore the roles of country concentration and industry concentration of the analyst's research portfolio in reducing the inefficient use of *MACRO* and *MACRO_F*. Sonney [2009] and Kini *et al.* [2009] document that the country and industry structure of an analyst's portfolio affects forecast accuracy differentially (see discussion in Section 2). It is possible that our measures of exposure similarity capture some degree of analyst country specialization. By including the country and industry concentrations, we differentiate our measures from the country specialization documented by Sonney [2009] and Kini *et al.* [2009]. We calculate the country concentration of analyst *i*'s portfolio in year *t*, HI_Cntry_{it}, as the sum of the squared sales percentage from each country for all firms in analyst *i*'s portfolio, $\sum_{n=1}^{N} (s^{n}_{it})^2$, where $s^{n}_{i,t}$ is the ratio of firms' sales in country *n* in year *t* to firms' total sales. We calculate the industry concentration, HI_Ind_{it}, in a similar fashion. We denote the ratio of firms' sales in industry *m* to total sales with e^{m}_{it}, $HI\_Ind_{it} = \sum_{m=1}^{M} (e^{m}_{it})^2$. We classify firms in industries using two-digit SIC codes and industry segment data from Compustat.

Our measures of country (industry) concentration differ from Sonney's specialization measures or Kini *et al.*'s diversification measures, as those studies assign each firm to a single country (industry). Due to these differences and Sonney [2009] and Kini *et al.* [2009]'s conflicting conclusions on the relation between specialization (diversification) and forecast accuracy, we do not make directional predictions regarding the relation between country (industry) concentration and efficient use of *MACRO_F*.

We also consider the following determinants of forecast efficiency and accuracy: firm-specific experience (Lim [2001]), $LogFIRMEXP_{ijt}$; broker size (Clement [1999]), $LogBRKSZ_{it}$; number of firms followed by the analyst (Clement, Frankel and Miller [2003]), $LogNFIRMS_{it}$, number of industries followed by the analyst (Clement *et al*. [2003]), $LogNIND_{it}$; and forecast horizon (Clement and Tse [2005]), $LogHRZN_{ijt}$. Finally, we include firm characteristics that affect the consensus forecast errors (see Section 4). We estimate the following regressions:

$$\begin{aligned} FE_{ijt} &= \alpha + \beta MACRO_{jt} + \gamma SIMEXP_{ij,t-1} + \rho MACRO_{jt} \times SIMEXP_{ij,t-1} \\ &\quad + \text{Analyst Controls} + \text{Firm Controls} + \varepsilon_{ijt} \end{aligned} \tag{5}$$

$$\begin{aligned} FE_{ijt} &= \alpha + \beta_1 MACRO\_F_{jt} + \gamma_1 SIMEXP\_F_{ij,t-1} + \rho_1 MACRO\_F_{jt} \times SIMEXP\_F_{ij,t-1} \\ &\quad + \beta_2 MACRO\_D_{jt} + \gamma_2 SIMEXP\_D_{ij,t-1} + \rho_2 MACRO\_D_{jt} \times SIMEXP\_D_{ij,t-1} \\ &\quad + \text{Analyst Controls} + \text{Firm Controls} + \varepsilon_{ijt} \end{aligned} \tag{6}$$

where the dependent variable is analyst *i*'s forecast error for firm *j* in year *t*, scaled by stock price; independent variables are defined above and in detail in Appendix I. Our variables of interest are the interaction terms $MACRO_{jt} \times SIMEXP_{ij,t-1}$ and $MACRO\_F_{jt} \times SIMEXP\_F_{ij,t-1}$. Based on the finding in Section 4 that analysts underreact to *MACRO* and *MACRO_F* information, we expect $\beta>0$ and $\beta_1>0$. Therefore, more efficient use of *MACRO* and *MACRO_F* indicates $\rho<0$ in equation (5) and $\rho_1<0$ in equation (6).

Table 2 panel B reports the descriptive statistics for the individual forecast sample used in this test. The mean individual forecast error is −0.027, the mean exposure similarity, $SIMEXP_{ij,t-1}$, is −0.250 and the mean foreign exposure similarity, $SIMEXP\_F_{ij,t-1}$, is −0.146. The average analyst has a country concentration of 0.338, an industry concentration of 0.578, follows 3.095 industries and 9.548 firms, makes forecasts at the horizon of 91 days, and has been following the firm for 3.709 years. The average broker employs 44 analysts. Similar to consensus forecast errors, individual forecast errors are positively correlated with *MACRO* (Table 2 panel D).

Table 5 reports the estimation results for equations (5) and (6). Column (1) reports the baseline regression. Consistent with our Section 4 findings of inefficient use of information at the consensus level, individual analysts significantly underreact to *MACRO* information, as evidenced by a slope coefficient of 0.066, significant at the 1% level. In column (2), where we estimate equation (5), the coefficient of the interaction term $MACRO_{jt} \times SIMEXP_{ij,t-1}$ is statistically significant at −0.149, consistent with our prediction that analysts who follow firms with similar country exposures use *MACRO* information more efficiently. The main effect of $SIMEXP_{ij,t-1}$ is positive and significant, 0.604 with a *t*-value of 3.48, suggesting that analysts whose portfolios are more similar in country exposures are, on average, less optimistic.

In column (3), we include *MACRO* interacted with country concentration and industry concentration. The coefficient on $MACRO_{jt} \times SIMEXP_{ij,t-1}$ remains significant at the 5% level; its value, −0.139, is similar to that in column (2). The coefficient on $MACRO_{jt} \times HI\_Cntry_{i,t-1}$ is negative but insignificant, while the coefficient of $MACRO_{jt} \times HI\_Ind_{i,t-1}$ is positive and significant, suggesting that either analyst's country concentration or industry concentration helps to reduce the inefficiency in use of *MACRO* information. In column (4), we further interact *MACRO* with other analyst characteristics and find that analyst's firm-specific experience and number of firms followed help reduce the inefficiency, but our variable of interest, $MACRO_{jt} \times SIMEXP_{ij,t-1}$, remains significant at the 5% level, and the magnitude of its coefficient remains approximately the same. The evidence in columns (3) and (4) suggests that our measure of country exposure similarity helps explain forecast efficiency beyond the analyst's country and industry concentrations and traditional analyst characteristics.

In columns (5)–(7) of Table 5, we estimate equation (6). The results indicate that individual analysts underreact to the foreign component of *MACRO*, *MACRO_F*, but the similarity in foreign exposures among analyst's research portfolios helps reduce such inefficiency. The coefficient on $MACRO\_F_{jt} \times SIMEXP\_F_{ij,t-1}$, is −0.243, significant at the 5% level, while the coefficient of $MACRO\_D_{jt} \times SIMEXP\_D_{ij,t-1}$ is insignificant. A one standard deviation increase in $SIMEXP\_F_{ij,t-1}$ from the sample mean corresponds to a reduction in the inefficiency regarding *MACRO_F* by 0.027, which is equivalent to a 35% reduction in the inefficiency[7]. An analyst's firm-specific experience and the number of firms followed also help reduce the inefficiency related to *MACRO_F*, while country and industry concentration do not.

In summary, individual forecasts are inefficient with respect to *MACRO* and *MACRO_F*. The inefficiency is reduced when analysts follow firms with similar foreign exposures, consistent with our conjecture that analysts benefit from economies of scale in the acquisition and processing of information about the foreign activities of the firms they cover.

5.2. Global expertise and forecast accuracy

In this section, we examine whether similarity in exposures *(SIMEXP)* is positively related with forecast accuracy. Our evidence that *SIMEXP* is positively associated with forecast efficiency regarding *MACRO* does not necessarily imply that it has a positive relation with accuracy: an analyst who efficiently uses one type of information may use another inefficiently (see Footnote #1), and the net effect on forecast accuracy remains uncertain.

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[7] The 35% is calculated by taking the first-order derivative of FE_{ijt} with respect to $MACRO\_F_{jt}$ in equation (6) and plugging in the sample mean and standard deviation of $SIMEXP\_F_{ij,t-1}$:

$$\frac{-0.243 \times \text{standard deviation of } SIMEXP\_F_{ij,t-1}}{0.043 - 0.243 \times \text{mean of } SIMEXP\_F_{ij,t-1}} = \frac{-0.243 \times 0.112}{0.043 - 0.243 \times (-0.146)} = -35\%.$$

Following Clement [1999], we control for the heterogeneity across firm years by demeaning the dependent and independent variables.[8] Specifically, we measure forecast accuracy as the proportional mean absolute forecast error, $PMAFE_{ijt} = AFE_{ijt} / \overline{AFE}_{jt} - 1$, where AFE_{ijt} is the absolute forecast error for analyst *i*'s forecast for firm *j* in year *t*, and $\overline{AFE}_{jt}$ is the mean absolute forecast error for firm *j* in year *t*. We then estimate the following regressions:

$$PMAFE_{ijt} = \alpha + \beta SIMEXP_{ij,t-1} + \text{Analyst Controls} + \varepsilon_{ijt} \tag{7}$$

$$PMAFE_{ijt} = \alpha + \beta_1 SIMEXP\_F_{ij,t-1} + \beta_2 SIMEXP\_D_{ij,t-1} + \text{Analyst Controls} + \varepsilon_{ijt}. \tag{8}$$

We include $LogFIRMEXP_{ijt}$, $LogNFIRMS_{it}$, $LogNIND_{it}$, $LogBRKSZ_{it}$, and $LogHRZN_{ijt}$ as analyst controls.

Table 6 column (1) reports the estimation of equations (7). The coefficient of the global expertise variable, *SIMEXP*, is −0.137, significant at the 1% level. Firm-specific experience and broker size also help improve forecast accuracy, while number of industries followed and forecast horizon reduce forecast accuracy. In column (2), we include country concentration, $HI\_Cntry_{i,t-1}$, and industry concentration, $HI\_Ind_{i,t-1}$, and our global expertise variable remains significantly negative, −0.183, significant at the 1% level. Country and industry concentrations also help improve forecast accuracy.

Column (3) reports the estimation of equation (8). *SIMEXP_F* is negative, −0.377, and significant at the 5% level. A one standard deviation increase in *SIMEXP_F* corresponds to a 1.6% decrease in absolute forecast errors. *SIMEXP_D* is also significant and negative, but its economic significance is much smaller, with a 0.5% decrease in absolute forecast errors for a one-standard deviation increase in *SIMEXP_D*. In column (4), we include $HI\_Cntry_{i,t-1}$ and $HI\_Ind_{i,t-1}$ and

[8] This approach is analogous to estimating a model with firm-year dummies.

reestimate equation (8). *SIMEXP_F* remains significant and negative, although its economic significance drops slightly. A one standard deviation increase in *SIMEXP_F* corresponds to a 1.2% decrease in absolute forecast errors. In comparison, a one standard deviation increase in an analyst's experience, *LogFIRMEXP*, corresponds to a 1.4% decrease in absolute forecast errors, and a one standard deviation increase in country concentration, $HI\_Cntry_{i,t-1}$, (industry concentration, $HI\_Ind_{i,t-1}$) corresponds to a 1.4% (2.0%) decrease in absolute forecast errors. This evidence suggests that an analyst's global expertise improves overall forecast accuracy, and the improvement is comparable to and beyond that of country and industry concentrations.

5.3. Global expertise and forecast informativeness

We now investigate whether analysts with global expertise issue more informative forecasts.[9] We estimate the following regressions of three-day market reactions to analyst forecast revisions on forecast revisions interacted with global expertise:

$$\begin{aligned} CAR_{ijt} &= \alpha + \beta NEWS_{ijt} + \gamma SIMEXP_{ij,t-1} + \varphi NEWS_{ijt} \times SIMEXP_{ij,t-1} \\ &+ \text{Firm Controls} + \text{Analyst Controls} + \varepsilon_{ijt} \end{aligned} \tag{9}$$

$$\begin{aligned} CAR_{ijt} &= \alpha + \beta_1 NEWS\_F_{ijt} + \gamma_1 SIMEXP\_F_{ij,t-1} + \varphi_1 NEWS\_F_{ijt} \times SIMEXP\_F_{ij,t-1} \\ &+ \beta_2 NEWS\_D_{ijt} + \gamma_2 SIMEXP\_D_{ij,t-1} + \varphi_2 NEWS\_D_{ijt} \times SIMEXP\_D_{ij,t-1} \\ &+ \text{Firm Controls} + \text{Analyst Controls} + \varepsilon_{ijt} \end{aligned} \tag{10}$$

where the dependent variable, CAR_{ijt}, is three-day cumulative abnormal returns, adjusted with the Fama-French three factors (Fama and French [1993]) and the momentum factor (Carhart [1997]), around analyst *i*'s EPS forecast revision for firm *j* in year *t*, multiplied by 100. $NEWS_{ijt}$ is the difference between analyst *i*'s EPS forecast for firm *j* in year *t* and the prevailing consensus forecast, scaled by stock price at the beginning of year *t*, then multiplied by 100. We further

[9] Our results that analysts with global expertise incorporate *MACRO* information more efficiently and produce more accurate forecasts suggest but do not guarantee that these forecasts convey new information to the market.

decompose $NEWS_{ijt}$ into domestic and foreign components, $NEWS\_D_{ijt}$ and $NEWS\_F_{ijt}$, by multiplying it with percentages of firm j's domestic and foreign sales in year $t-1$, respectively. We expect the coefficients on the interaction terms, φ and φ_1, to be positive. We include the analyst and firm controls appearing in the previous sections: $LogFIRMEXP_{ijt}$, $LogBRKSZ_{it}$, $LogNFIRMS_{it}$, $LogNIND_{it}$, $LogHRZN_{ijt}$, $GDPDISP_{ijt}$, $\Delta ROA_{j,t-1}$, $STDROA_{j,t-1}$, $LOGMV_{j,t-1}$, $BTM_{j,t-1}$, $LEV_{j,t-1}$, $IOR_{j,t-1}$, $LOSS_{j,t-1}$, $ANNRET_{j,t-1}$, and $ACCRUA_{j,t-1}$, as well as industry and year fixed effects.

The mean (median) three-day market reaction to individual forecast revisions, CAR_{ijt}, is −9.8 (7.1) basis points, and the standard deviation is 7.297 percent, as reported in Table 2 panel B. The mean news contained in individual forecast revisions is −0.089% of the stock price, and the median is zero. The mean foreign (domestic) news is −0.049% (−0.040%) of the stock price. The correlation between CAR_{ijt} and $NEWS_{ijt}$ is significantly positive, as expected.

Table 7 columns (1) and (4) report the estimation of equations (9) and (10), respectively. The coefficients on $NEWS_{ijt}$, $NEWS\_F_{ijt}$, and $NEWS\_D_{ijt}$ are significantly positive, suggesting that forecast revisions convey new information to the market. The coefficient φ of the interaction between news and global expertise, $NEWS_{ijt} \times SIMEXP_{ij,t-1}$, is positive at 0.765 and significant at the 1% level, and the coefficient φ_1 of the interaction, $NEWS\_F_{ijt} \times SIMEXP\_F_{ij,t-1}$, is positive at 1.978 and significant at the 1% level, suggesting that the market reacts more strongly to forecasts issued by analysts with global expertise. A one standard deviation increase in $SIMEXP\_F_{ij,t-1}$ from the sample mean increases the market reaction to forecast revisions by 11%.[10] In columns (2) and (5), we include interactions of $NEWS_{ijt}$ and $NEWS\_F_{ijt}$ with country and industry concentration,

[10] The 11% is calculated by taking the first-order derivative of CAR_{ijt} with respect to $NEWS\_F_{ijt}$ in equation (10) and plugging in the sample mean and standard deviation of $SIMEXP\_F_{ij,t-1}$:

$$\frac{1.978 \times \text{standard deviation of } SIMEXP\_F_{ij,t-1}}{2.375 + 1.978 \times \text{mean of } SIMEXP\_F_{ij,t-1}} = \frac{1.978 \times 0.112}{2.375 + 1.978 \times (-0.146)} = 11\%.$$

and in columns (3) and (6), we further include interactions of $NEWS_{ijt}$ and $NEWS\_F_{ijt}$ with other analyst characteristics. We find no evidence that country and industry concentrations, firm-specific experience, broker size, or number of firms followed is associated with forecast informativeness. The evidence suggests that analysts with global expertise produce more informative forecasts.

5.4. Global expertise and all-star ranking

Finally, we explore whether analyst global expertise is positively associated with the likelihood of an analyst being ranked as an all-star (First, Second, or Runner-Up) in the Institutional Investor Magazine annual poll. All-star ranking is a widely accepted measure of analyst reputation and a determinant of analyst compensation even after controlling for other important performance metrics (Groysberg *et al.* [2011]), making it an effective proxy for analyst incentives.

We model the probability of an analyst being ranked as all-star in year t+1 as a function of analyst characteristics measured in year t:

$$Logit(STAR_{i,t+1}) = \alpha + \beta SIMEXP_{it} + \text{Analyst Controls} + \varepsilon_{i,t+1} \tag{11}$$

$$Logit(STAR_{i,t+1}) = \alpha + \beta_1 SIMEXP\_F_{it} + \beta_2 SIMEXP\_D_{it} + \text{Analyst Controls} + \varepsilon_{i,t+1} \tag{12}$$

where $STAR_{i,t+1}$ equals one if analyst i is ranked as First, Second, or Runner-Up by Institutional Investor magazine in year t+1, and zero otherwise. We measure $SIMEXP_{it}$, $SIMEXP\_F_{it}$, and $SIMEXP\_D_{it}$ as the means of $SIMEXP_{ijt}$, $SIMEXP\_F_{ijt}$, and $SIMEXP\_D_{ijt}$ across all firms j that analyst i covers in year t. As controls, we include country and industry concentrations, HI_Cntry_{it} and HI_Ind_{it}; broker size, $LogBRKSZ_{it}$; number of firms followed, $LogNFIRMS_{it}$; number of industries followed, $LogNIND_{it}$; and analyst's general experience, $LogGENEXP_{it}$. We also control for Leader-Follower ratio (Cooper, Day and Lewis [2001]), LFR_{it}; forecast accuracy (Hong *et al.*

[2000]), ACC_{it}; boldness (Rees, Sharp and Twedt [2014]), $BOLD_{it}$; forecast frequency (Jacob, Lys and Neale [1999], Emery and Li [2009]), $FREQ_{it}$; percentage of optimistic forecasts issued (Hong and Kubik [2003]), OPT_{it}; firm size (Stickel [1995]), $LogMV_{it}$; and institutional holding (O'Brien and Bhushan [1990]), IOR_{it}. See Appendix I for detailed variable definitions. Table 1 panel C reports the descriptive statistics for this sample.

Table 8 columns (1) and (4) report the estimation of equations (11) and (12), respectively. The coefficients on $SIMEXP_{it}$ and $SIMEXP\_F_{it}$ are 1.015 and 1.585, respectively, both significant at the 1% level, suggesting that an analyst with global expertise is more likely to be ranked as an all-star. A one standard deviation increase in $SIMEXP\_F_{it}$ increases the probability of being ranked all-star by 0.5 percent, a 5% increase in the probability of being ranked from the sample mean of 11.2 percent.

We also examine the changes in all-star rankings. We define $STAR\_UP_{i,t+1}$ = 1 if analyst *i* is not ranked all-star in year *t* but ranked in year *t*+1, and zero otherwise; $STAR\_DOWN_{i,t+1}$ = 1 if analyst *i* is ranked all-star in year *t* but not ranked in year *t*+1, and zero otherwise. We reestimate equations (11) and (12) with $STAR\_UP_{i,t+1}$ and $STAR\_DOWN_{i,t+1}$ as dependent variables and report the results in Table 8 columns (2)–(3) and (5)–(6). We find a significant and negative effect of global expertise in losing all-star ranking. The coefficient on $SIMEXP\_F_{it}$ in the regression of $STAR\_DOWN_{i,t+1}$ is −1.552, significant at the 5% level. A one-standard deviation increase in $SIMEXP\_F_{it}$ results in a 3.3 percent reduction in the probability of losing all-star ranking, a 12% decrease from the mean probability of 27.3 percent. We find no evidence that global expertise is associated with gaining all-star ranking. Overall, the evidence suggests that brokerages and institutional investors value analysts' global expertise and that analysts can develop global expertise to distinguish themselves from other analysts.

5.5. Robustness checks

In our main analysis, we value-weight pair-wise similarity measures to construct our global expertise measure. An alternative measure of similarity, $SIMEXP2_{ijt}$, can be constructed by viewing all firms in analyst *i*'s portfolio as a single hypothetical firm and calculating the distance between firm *j*'s exposure and the hypothetical firm's exposure. See Appendix II for illustrations. We replicate our analyses in Sections 5.1–5.4 using this alternative measure and report the results in Table 9. All our previous inferences are maintained. In particular, we find that *SIMEXP2* is associated with greater forecast efficiency regarding *MACRO* information, higher forecast accuracy, greater forecast news informativeness, and generally better analyst career outcomes.

In untabulated analysis, we conduct tests on a subsample of firm-years where analysts initiate new coverage to illustrate that our similarity measure (*SIMEXP*) captures analyst expertise that applies to new tasks and not just familiarity with existing coverage. Consistent with our expectation, for this sample of newly added stocks, we find that analyst global expertise is significantly associated with greater efficiency in analyst use of *MACRO* information, higher forecast accuracy and higher informativeness of forecast news.

6. Conclusions

While there is much interest in understanding the determinants of analyst earnings forecast performance, relatively little is known about how globalization affects the task of forecasting earnings and basic performance measures such as efficiency, accuracy, and price informativeness. As US firms increasingly derive their profits in foreign markets, research in this area takes on added urgency.

A unique forecasting challenge posed by globalization is that information relevant to forecasting earnings increasingly transcends national borders, which means that to forecast earnings, the analyst must accurately assess firm exposures to multiple foreign countries and all of these countries' growth prospects. We show that sell-side consensus and sell-side individual forecasts do not efficiently use available information regarding country exposures and expected country GDP growth. Country-specific factors that contribute to consensus forecast efficiency include proximity to the US, economic importance to the firm, and visibility, consistent with theories of limited attention and information processing cost (Hirshleifer and Teoh [2003], Sims [2003]). At the individual forecast level, forecast efficiency is positively related to the similarity in exposure between the firm and the rest of the firms in the analyst portfolio, suggesting economy of scales benefits from covering similar firms. Finally, following firms with similar country exposures is associated with higher accuracy, informativeness, and likelihood of being ranked as an all-star analyst in the Institutional Investor Magazine annual poll. Our results that an appropriately structured research portfolio allows an analyst to issue more informative forecasts and achieve the coveted all-star rank suggest globalization not only poses a challenge but also creates an opportunity for research providers and analysts to distinguish themselves.

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Appendix I. Variable Definitions

Variable		Definition
Consensus and individual forecast sample		
A_{jt}	=	Actual earnings per share (EPS) of firm *j* in year *t*, scaled by stock price at the beginning of year *t*, then multiplied by 100 (in percentage).
F_{ijt}	=	Analyst *i*'s EPS forecast for firm *j* in year *t*, scaled by stock price at the beginning of year *t*, then multiplied by 100 (in percentage). Analyst *i*'s EPS forecast is taken as the last forecast before year *t* end.
$Cons_{jt}$	=	Consensus (median) forecast for firm *j* in year *t*, scaled by stock price at the beginning of year *t*, then multiplied by 100 (in percentage). The consensus is constructed using the first forecast issued by each analyst right after year $t-1$'s earnings announcements.
FE_{ijt}	=	Forecast error for analyst *i*'s EPS forecast for firm *j* in year *t*, calculated as actual EPS minus analyst *i*'s forecast EPS, scaled by stock price at the beginning of year *t*, then multiplied by 100 (in percentage), i.e., $A_{jt} - F_{ijt}$. We keep analyst *i*'s last forecast before year *t* end but after year $t-1$'s earnings announcements.
CFE_{jt}	=	Consensus forecast error for firm *j* in year *t*, calculated as actual EPS minus analysts' consensus forecast EPS, scaled by stock price at the beginning of year *t*, then multiplied by 100 (in percentage), i.e., $A_{jt} - Cons_{jt}$.
$PMAFE_{ijt}$	=	Proportional mean forecast error for analyst *i*'s forecast for firm *j* in year *t*, calculated as $AFE_{ijt} / \overline{AFE}_{jt} - 1$, where AFE_{ijt} is the absolute forecast error for analyst *i*'s forecast for firm *j* in year *t*, and $\overline{AFE}_{jt}$ is the mean absolute forecast error for firm *j* in year *t*.
CAR_{ijt}	=	three-day cumulative abnormal returns adjusted for Fama-French's Four Factors in the window [−1,+1] of analyst *i*'s EPS forecast for firm *j* in year *t*, in percentage.
$NEWS_{ijt}$	=	Difference between analyst *i*'s EPS forecast for firm *j* in year *t* and prevailing consensus forecast, scaled by stock price at the beginning of year *t*, then multiplied by 100.
$NEWS\_D_{ijt}$	=	Domestic component of news contained in analyst *i*'s EPS forecast for firm *j* in year *t*, calculated as $NEWS_{ijt}$ multiplied by percentage of domestic sales of firm *j* in year $t-1$.
$NEWS\_F_{ijt}$	=	Foreign component of news contained in analyst *i*'s EPS forecast for firm *j* in year *t*, calculated as $NEWS_{ijt}$ multiplied by percentage of *foreign* sales of firm *j* in year $t-1$.
$MACRO_{jt}$	=	Sum product of firm *j*'s *N* country exposures and the respective one year ahead International Monetary Fund (IMF) country GDP growth forecasts. Country exposures is the vector $S_{j,t-1} = \left(s^1_{j,t-1}, s^2_{j,t-1}, \cdots, s^N_{j,t-1}\right)$, where each element is firm *j*'s country sales in year $t-1$, scaled by total sales. $G_{jt} = \left(g^1_{jt}, g^2_{jt}, \cdots, g^N_{jt}\right)$ is the vector of GDP growth forecasts in year *t*, in percentage. $MACRO_{jt} = S_{j,t-1} \cdot G_{jt}$ $= \sum_{n=1}^{N} s^n_{j,t-1} \times g^n_{jt}$. The country sales data are extracted from Compustat Segment Data. For sales reported at a regional level, we decompose it into the region's member countries using a GDP-based weighting scheme. See Appendix II for a simple example.

Appendix I. Variable Definitions (cont'd)

Variable		Definition
$MACRO\_D_{jt}$	=	Product of firm *j*'s domestic exposure in year $t-1$ and the one year ahead domestic GDP growth forecast, in percentage.
$MACRO\_F_{jt}$	=	Sum product of firm *j*'s *foreign* country exposures and the one year ahead respective foreign country GDP growth forecasts, $\sum_{n \neq US}^{N} s_{j,t-1}^{n} \times g_{jt}^{n}$, in percentage. $MACRO\_F_{jt} + MACRO\_D_{jt} = MACRO_{jt}$.
$MACRO\_F\_Top5_{jt}$	=	Sum product of firm *j*'s five largest *foreign* country exposures and the one year ahead respective GDP growth forecasts.
$MACRO\_F\_NonTop5_{jt}$	=	Complement of $MACRO\_F\_Top5_{jt}$, calculated as $MACRO\_F_{jt} - MACRO\_F\_Top5_{jt}$.
$MACRO\_F\_Close5_{jt}$	=	Sum product of firm *j*'s exposures to the five *foreign* countries closest to the US in year $t-1$ and the one year ahead respective country GDP growth forecasts.
$MACRO\_F\_NonClose5_{jt}$	=	Complement of $MACRO\_F\_Close5_{jt}$, calculated as $MACRO\_F_{jt} - MACRO\_F\_Close5_{jt}$.
$MACRO\_F\_Cov5_{jt}$	=	Sum product of firm *j*'s exposures to the five *foreign* countries with the highest analyst coverage in year $t-1$ and the one year ahead GDP growth forecast of the respective countries. We calculate a country's analyst coverage by summing over the coverage of all firms with exposures to the respective country.
$MACRO\_F\_NonCov5_{jt}$	=	Complement of $MACRO\_F\_Cov5_{jt}$, calculated as $MACRO\_F_{jt} - MACRO\_F\_Cov5_{jt}$.
$MACRO\_F\_Cntry_{jt}$	=	$MACRO\_F_{jt}$ only for countries reported by firm *j* at the specific *country* level in year $t-1$.
$MACRO\_F\_Reg_{jt}$	=	$MACRO\_F_{jt}$ only for regions reported by firm *j* at the *regional* level in year $t-1$. We construct the regional GDP growth forecasts from individual member countries' GDP shares and growth forecasts. $MACRO\_F\_Cntry_{jt} + MACRO\_F\_Reg_{jt} = MACRO\_F_{jt}$.
$MACRO\_F\_HiXps_{jt}$	=	$MACRO\_F_{jt}$, if firm *j*'s percentage of foreign sales is in the top quartile of the sample in year $t-1$; 0 otherwise.
$MACRO\_F\_LoXps_{jt}$	=	$MACRO\_F_{jt}$, if firm *j*'s percentage of foreign sales is in the bottom three quartiles of the sample in year $t-1$; 0 otherwise.
$SIMEXP_{ijt}$	=	Similarity in country exposures between firm *j* and all other firms in analyst *i*'s portfolio in year *t*. We first calculate the distance in exposures between firm *j* and firm *k* as $DIST_{jkt} = \sqrt{\sum_{n=1}^{N} (s_{jt}^{n} - s_{kt}^{n})^2}$. We then calculate the value-weighted average of $DIST_{j,k,t,}$, with the weights given by firm *k*'s market value divided by the collective market value, multiplied by −1. See Appendix II for a simple example.

Appendix I. Variable Definitions (cont'd)

Variable		Definition
SIMEXP_D$_{ijt}$	=	Similarity between firm *j*'s *domestic* exposure and all other firms in analyst *i*'s portfolio in year *t*. We first calculate the distance in domestic exposures between firm *j* and firm *k* as $DIST^{D}_{jkt} = \left\| s^{US}_{jt} - s^{US}_{kt} \right\|$. We then calculate the value-weighted average of $DIST^{D}_{jkt}$, with the weights given by firm *k*'s market value divided by the collective market value, multiplied by −1.
SIMEXP_F$_{ijt}$	=	Similarity between firm *j*'s *foreign* exposure and all other firms in analyst *i*'s portfolio in year *t*. We first calculate the distance in *foreign* exposures between firm *j* and firm *k* as $DIST^{F}_{jkt} = \sqrt{\sum^{N}_{n \neq US} (s^{n}_{jt} - s^{n}_{kt})^2}$. We then calculate the value-weighted average of $DIST^{F}_{j,k,t}$, with the weights given by firm *k*'s market value divided by the collective market value, multiplied by −1.
SIMEXP2$_{ijt}$	=	Similarity in country exposures between firm *j*, S_{jt}, and all the firms in analyst *i*'s portfolio, viewed as a single hypothetical firm, S_{it}, $-\left\| S_{it} - S_{jt} \right\| = -\sqrt{\sum^{N}_{n=1} (s^{n}_{it} - s^{n}_{jt})^2}$, where each element of S_{it} , s^{n}_{it}, is the ratio of the firms' sales in country *n* in year *t* divided by firms' total sales. See Appendix II for a simple example.
SIMEXP2_D$_{ijt}$	=	Similarity between firm *j*'s *domestic* exposure and all other firms in analyst *i*'s portfolio when viewed as a single hypothetical firm, $-\left\| s^{US}_{it} - s^{US}_{jt} \right\|$, where s^{US}_{it} is the ratio of firms' sales in the US in year *t* divided by firms' total sales.
SIMEXP2_F$_{ijt}$	=	Similarity between firm *j*'s *foreign* exposures, S^{F}_{jt}, and all the firms in analyst *i*'s portfolio when viewed as a single hypothetical firm, S^{F}_{it} , $-\left\| s^{US}_{it} - s^{US}_{jt} \right\|$ $-\sqrt{\sum^{N}_{n \neq US} (s^{n}_{it} - s^{n}_{jt})^2}$, where s^{n}_{it} is the ratio of firms' sales in foreign country *n* in year *t* divided by firms' total sales.
HI_Cntry$_{it}$	=	Country concentration of analyst *i*'s portfolio in year *t*, calculated by $\sum^{N}_{n=1} (s^{n}_{it})^2$, where s^{n}_{it} is the ratio of firms' sales in country *n* in year *t* to firms' total sales.
HI_Ind$_{it}$	=	Industry concentration of analyst *i*'s portfolio in year *t*, calculated similarly to *HI_Cntry$_{it}$*. Denoting the ratio of firms' sales in industry *m* to total sales with e^{m}_{it} , $HI\_Ind_{it} = \sum^{M}_{m=1} (e^{m}_{it})^2$. Industry classification is based on two-digit SIC code, and we identify all industries each firm operates in using industry segment data from Compustat.
HRZN$_{ijt}$	=	Analyst *i*'s forecast horizon for firm *j* in year *t*, defined as the number of days from the analyst's forecast to the fiscal year end.
BRKSZ$_{it}$	=	Brokerage size, defined as the number of analysts employed by the brokerage at year *t*.

Appendix I. Variable Definitions (cont'd)

Variable		Definition
$FIRMEXP_{ijt}$	=	Firm-specific experience, defined as the number of years analyst *i* has covered firm *j*.
$NFIRMS_{it}$	=	Number of firms followed by analyst *i* in year *t*.
$NIND_{it}$	=	Number of industries followed by analyst *i* in year *t*. Industry classification is based on two-digit SIC code of each firm's primary industry.
$GDPDISP_{jt}$	=	Cross-sectional dispersion of GDP growth forecasts for year *t* for all countries firm *j* operates in.
ΔROA_{jt}	=	Change of *ROA* for firm *j* in year *t*.
$STDROA_{jt}$	=	Standard deviation of *ROA* for firm *j* in the past five years $t-4$ to *t*.
$LogMV_{jt}$	=	Natural logarithm of firm *j*'s market capitalization at the end of year *t*.
BTM_{jt}	=	Firm *j*'s book-to-market ratio at the end of year *t*.
$LOSS_{jt}$	=	1 if firm *j*'s earnings before extraordinary items are negative in year *t*; 0 otherwise.
LEV_{jt}	=	Firm *j*'s financial leverage at the beginning of year *t*.
IOR_{jt}	=	Institutional ownership of firm *j* at the beginning of year *t*.
$ACCRUAL_{jt}$	=	Firm *j*'s accruals in year *t*, scaled by book value of equity at the end of year *t*.
$LOSS_{jt}$	=	Dummy for negative earnings for firm *j* in year *t*.
D_DIV_{jt}	=	Dummy for firm *j* paying dividends in year *t*.
$ANNRET_{jt}$	=	Annual size-adjusted abnormal returns for firm *j* in year *t*.
DY_{jt}	=	Firm *j*'s dividend yield in year *t*.
All-star ranking sample		
$STAR_{i,t+1}$	=	1 if analyst *i* is ranked as First, Second, or Runner-Up by Institutional Investor magazine in year t+1, and zero otherwise.
$STAR\_UP_{i,t+1}$	=	1 if analyst *i* is not ranked by Institutional Investor magazine in year *t* but ranked in year t+1, and zero otherwise. This variable is missing for analysts who are ranked in year *t*.
$STAR\_DOWN_{i,t+1}$	=	1 if analyst *i* is ranked by Institutional Investor magazine in year *t* but not ranked in year t+1, and zero otherwise. This variable is missing for analysts who are not ranked in year *t*.
LFR_{it}	=	Leader-Follower ratio of analyst *i* in year *t*. Following Cooper *et al.* [2001], for each forecast made by analyst *i* in year *t*, we identify the five preceding and five subsequent forecasts issued by other analysts. We calculate the forecast's LFR as T0/T1, where T0 (T1) is the cumulative number of days by which the preceding (following) forecasts lead (lag) the forecast of interest. LFR_{it} is the average of LFRs of all forecasts issued by analyst *i* in year *t*.
ACC_{it}	=	Analyst *i*'s accuracy in year *t*. Following Hong *et al.* [2000], we sort analysts that follow firm *j* in year *t* based on their absolute forecast errors. We transform the sorting into a ranking, assigning 1 (0) to the highest (lowest) accuracy, and then average the ranks across all firms followed by analyst *i* in year *t*.

Appendix I. Variable Definitions (cont'd)

Variable		Definition
$BOLD_{it}$	=	Boldness. We sort all forecasts for firm *j* in year *t* based on the absolute value of their deviation from the consensus, defined as Rees *et al.* [2014]. We transform the sorting into a ranking, assigning 1 (0) to the largest (smallest) deviations. Averaging these ranks over all firms followed by analyst *i* in year *t* yields $BOLD_{it}$.
OPT_{it}	=	Percentage of optimistic (greater than actual earnings) forecasts issued by analyst *i* in year *t*.
$LogGENEXP_{it}$	=	General experience, defined as the natural logarithm of the number of years since analyst *i* first appears in IBES.
$FMVR_{it}$	=	First mover measure. The first analyst who issues a forecast for firm *j* in year *t* is given a score of 1; all other analysts are given scores of zero. Averaging scores across all firms followed by analyst *i* in year *t* yields $FMVR_{it}$.
$FREQ_{it}$	=	Forecast frequency. We first calculate the difference between the number of forecasts issued by analyst *i* for firm *j* in year *t* and the average number of forecasts issued by all other analysts for the same firm-year, $FREQ_{ijt}$. We then average across all firms followed by analyst *i* in year *t*.

Appendix II. A Numerical Example

We provide a simple numerical example to illustrate the calculation of the key variables, *MACRO*, *SIMEXP*, and *SIMEXP2*. In view of the simplicity of the example, we do not use any subscripts.

An analyst forecasts the earnings of firms A, B, and C. These firms have sales in the US, the UK, and China, as follows (percentage in parentheses):

	Firm A	Firm B	Firm C
US sales	\$50M (50%)	\$10M (20%)	\$25M (33%)
UK sales	\$30M (30%)	\$40M (80%)	
China sales	\$20M (20%)		\$50M (67%)
Total sales	\$100M (100%)	\$50M (100%)	\$75M (100%)
Market value	\$80M	\$40M	\$60M

Furthermore, assume that the GDP growth forecasts for the US, UK, and China in year *t* are 2%, 5%, and 10%, respectively.

MACRO$_A$

Firm A's exposures to the US, UK, and China are measured by firm A's US, UK, and China sales, each scaled by firm A's total sales: 50%, 30%, and 20%, respectively.

We calculate $MACRO_A$ as the product of the country exposures and country GDP growth forecasts: $MACRO_A = 50\% \times 2\% + 30\% \times 5\% + 20\% \times 10\% = 4.5\%$.

The domestic and foreign portions of $MACRO_A$ are $MACRO\_D_A = 50\% \times 2\% = 1\%$ and $MACRO\_F_A = 30\% \times 5\% + 20\% \times 10\% = 3.5\%$.

SIMEXP$_A$

The distance between A's and B's and between A's and C's country exposures are calculated as:

$$DIST_{A,B} = \sqrt{(50\%-20\%)^2 + (30\%-80\%)^2 + (20\%-0\%)^2} = 0.6164$$

$$DIST_{A,C} = \sqrt{(50\%-33\%)^2 + (30\%-0\%)^2 + (20\%-67\%)^2} = 0.5994.$$

The similarity in exposures between firm A and the other firms in the analyst portfolio, B and C, is $SIMEXP_A$, which is the value-weighted sum of $DIST_{A,B}$ and $DIST_{A,C}$, with the weights given by firm B and C's market values as percentages of their collective market value:

$$SIMEXP_A = \left(\frac{40}{40+60} \times DIST_{A,B} + \frac{60}{40+60} \times DIST_{A,C} \right) \times (-1) = -0.6062.$$

SIMEXP2$_A$

Viewing firms A, B, and C as a single hypothetical firm, ABC, we calculate ABC's country exposures as:

$$S = \begin{pmatrix} (50+10+25)/(100+50+75) \\ (30+40+0)/(100+50+75) \\ (20+0+50)/(100+50+75) \end{pmatrix} = \begin{pmatrix} 37.8\% \\ 31.1\% \\ 31.1\% \end{pmatrix}.$$

Intuitively, ABC's exposure to the US is the sum of A, B, and C's US sales, divided by the sum of A, B, and C's total sales. The similarity between Firm A's exposure and ABC's exposure, therefore, is:

$$SIMEXP2_A = \sqrt{(50\%-37.8\%)^2 + (30\%-31.1\%)^2 + (20\%-31.1\%)^2} \times (-1) = -0.1653.$$

Figure 1. Globalization Trend of US Firms

This figure shows the globalization trend of US firms from 1998 to 2014. The sample consists of all US firms listed on the NYSE or NASDAQ with data available from Compustat. This figure shows the time trends of the following: percentage of firms with foreign sales, percentage of firms with significant (>=25%) foreign sales, mean percentage of foreign sales for firms with foreign sales, and market capitalization of firms with significant foreign sales as a percentage of total market capitalization.

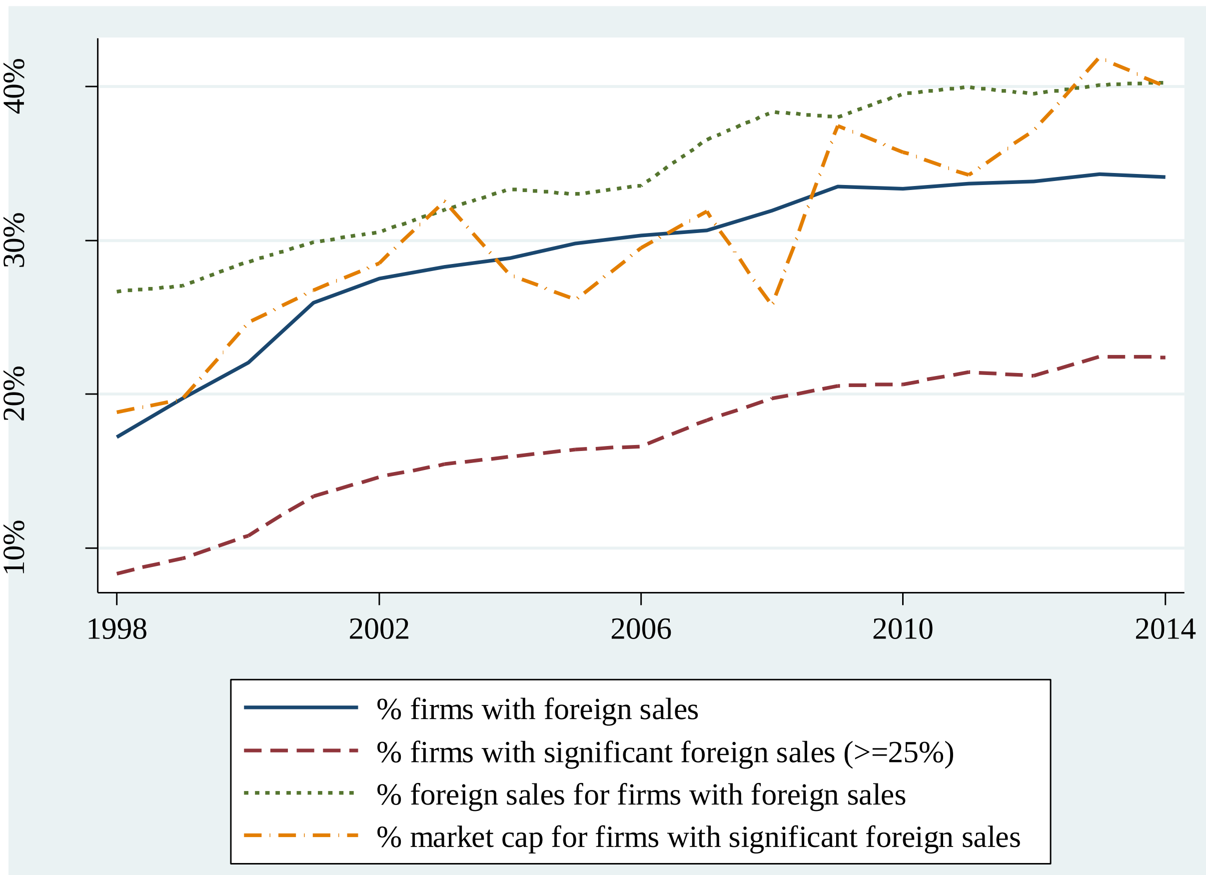

Table 1. Sample Selection

This table reports the sample selection procedures and the number of observations, firms, and analysts that remained after each step.

Procedure		#Obs.	#Firms	#Analysts
Compustat				
1.	Observations from Compustat Annual Fundamental North America with non-missing sales and total assets in the period 1998–2014	99,274	13,209	
2.	Merge with CRSP permno and IBES ticker	91,425	11,132	
3.	Delete observations with missing earnings announcement dates for year *t* and year $t-1$.	84,312	10,646	
4.	Merge with Geographic Segment data.	61,862	8,682	
5.	Delete firm-years whose aggregated segment sales differ from consolidated sales by more than 5%, foreign sales are larger than 100%.	55,246	8,545	
	→ Sample for **Figure 1.**			
6.	Delete observations with foreign sales less than 25%.	18,878	3,322	
7.	Delete observations with stock price less than $1, total assets less than $5 million, book value of equity less than $1 million, and total market value less than $10 million.	17,503	3,160	
8.	Merge with IMF GDP growth forecasts, construct *MACRO*, and delete observations with missing *MACRO*.	13,059	2,505	
I/B/E/S				
9.	Individual EPS forecasts for year *t* between year $t-1$'s earnings announcement date and year *t*'s fiscal year end with actual EPS data available for both years from I/B/E/S US file for the period 1999–2014.	1,672,617	6,692	13,522
10.	Construct the first consensus immediately after year $t-1$'s earnings announcements for each firm year.	1,672,617	6,692	13,522
11.	Keep only the last forecast from each individual analyst for each firm year.	465,853	6,692	13,522
12.	Merge with Compustat data from step 8.	106,756	1,714	7,788
13.	Merge with CRSP stock price and return data.	106,042	1,672	7,736
	→ Keep one observation per firm year, and construct the sample analyzed in **Tables 3–4** (Consensus Sample).	9,843	1,672	
14.	Construct *SIMEXP* and delete observations with missing *SIMEXP*.	82,754	1,554	5,103
	→ Sample analyzed in **Tables 5–7** (Individual Analyst Sample)			
15.	Merge with Institutional Investor all-star ranking.	82,754	1,554	5,103
	→ Keep one observation per analyst-year and construct the all-star ranking sample analyzed in **Table 8** (All-star Ranking Sample).	22,737		5,103

Table 2. Descriptive Statistics

This table reports the descriptive statistics for the consensus forecasts sample (panel A), the individual forecasts sample (panel B), the analyst all-star ranking sample (panel C), and pair-wise correlations for the individual forecasts sample (panel D) for the period 1999–2014. See Appendix I for variable definitions. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A. Consensus forecast sample

	Count	Mean	Std. Dev.	P25	Median	P75
A_{jt}	9843	3.752	6.576	2.196	4.856	7.030
$Cons_{jt}$	9843	4.455	7.257	2.949	5.189	7.094
CFE_{jt}	9843	-0.914	4.824	-1.091	-0.019	0.445
$MACRO_{jt}$	9843	2.462	1.653	2.007	2.692	3.332
$MACRO\_D_{jt}$	9734	1.119	1.009	0.527	1.178	1.733
$MACRO\_F_{jt}$	9835	1.358	1.228	0.790	1.231	1.827
$MACRO\_F\_Top5_{jt}$	9835	0.803	1.145	0.339	0.557	0.937
$MACRO\_F\_NonTop5_{jt}$	9843	0.557	0.477	0.291	0.550	0.846
$MACRO\_F\_Close5_{jt}$	9835	0.081	0.542	0.001	0.002	0.006
$MACRO\_F\_NonClose5_{jt}$	9532	1.299	1.171	0.769	1.210	1.783
$MACRO\_F\_Cov5_{jt}$	9835	0.242	0.504	0.095	0.179	0.293
$MACRO\_F\_NonCov5_{jt}$	9528	1.125	1.088	0.575	0.988	1.535
$MACRO\_F\_Cntry_{jt}$	9843	0.471	1.137	0.000	0.000	0.458
$MACRO\_F\_Reg_{jt}$	9843	0.942	0.897	0.417	0.919	1.421
$MACRO\_F\_HiXps_{jt}$	9836	0.565	1.316	0.000	0.000	0.000
$MACRO\_F\_LoXps_{jt}$	9842	0.792	0.820	0.000	0.871	1.339
$LogMV_{j,t-1}$	9843	7.273	1.767	5.985	7.123	8.425
$BTM_{j,t-1}$	9843	0.494	0.329	0.257	0.422	0.642
$LOSS_{j,t-1}$	9843	0.225	0.418	0.000	0.000	0.000
$D\_DIV_{j,t-1}$	9843	0.419	0.493	0.000	0.000	1.000
$DY_{j,t-1}$	9843	2.464	8.194	0.000	0.000	0.879
$STDROA_{j,t-1}$	9016	0.063	0.070	0.019	0.038	0.079
$LEV_{j,t-1}$	9787	0.176	0.165	0.008	0.152	0.287
$IOR_{j,t-1}$	9843	0.625	0.289	0.477	0.707	0.841
$ANNRET_{j,t-1}$	9841	0.073	0.515	-0.230	-0.013	0.243
$ACCRUAL_{j,t-1}$	9842	-0.147	0.260	-0.180	-0.091	-0.030
$GDPDISP_{jt}$	9834	3.249	1.141	2.576	2.975	3.778

Panel B. Individual forecast sample

	Count	Mean	Std. Dev.	P25	Median	P75
FE_{ijt}	82754	-0.027	1.236	-0.082	0.048	0.232
CAR_{ijt}	82754	-0.098	7.297	-3.416	0.071	3.593
$NEWS_{ijt}$	81413	-0.089	0.864	-0.165	0.000	0.140
$NEWS\_D_{ijt}$	81413	-0.040	0.421	-0.068	0.000	0.060
$NEWS\_F_{ijt}$	81413	-0.049	0.519	-0.080	0.000	0.067
$MACRO_{jt}$	82754	2.501	1.637	2.081	2.764	3.339
$MACRO\_D_{jt}$	82754	1.076	0.968	0.540	1.158	1.645
$MACRO\_F_{ijt}$	82754	1.427	1.213	0.883	1.319	1.897
$SIMEXP_{ij,t-1}$	82754	-0.250	0.133	-0.314	-0.223	-0.154
$SIMEXP\_D_{ij,t-1}$	82754	-0.171	0.110	-0.224	-0.148	-0.093
$SIMEXP\_F_{ij,t-1}$	82754	-0.146	0.112	-0.197	-0.107	-0.065
$SIMEXP2_{ij,t-1}$	82754	-0.226	0.140	-0.297	-0.197	-0.119
$SIMEXP2\_D_{ij,t-1}$	82754	-0.160	0.131	-0.226	-0.126	-0.060
$SIMEXP2\_F_{ij,t-1}$	82754	-0.128	0.108	-0.170	-0.091	-0.053
$HI\_Cntry_{i,t-1}$	82754	0.338	0.198	0.195	0.292	0.437
$HI\_Ind_{i,t-1}$	82754	0.578	0.260	0.363	0.522	0.820
$BRKSZ_{it}$	82754	44.429	30.269	18.000	38.000	71.000
$HRZN_{ijt}$	82754	91.040	70.268	57.000	67.000	87.000
$FIRMEXP_{ijt}$	82754	3.709	2.796	2.000	3.000	5.000
$NFIRMS_{it}$	82754	9.548	4.738	6.000	9.000	12.000
$NIND_{it}$	82754	3.095	1.907	2.000	3.000	4.000

Panel C. Analyst all-star ranking sample

	Count	Mean	Std. Dev.	P25	Median	P75
$STAR_{i,t+1}$	22737	0.112	0.315	0.000	0.000	0.000
$STAR\_UP_{i,t+1}$	19857	0.022	0.148	0.000	0.000	0.000
$STAR\_DOWN_{i,t+1}$	2880	0.273	0.445	0.000	0.000	1.000
$SIMEXP_{it}$	22737	-0.281	0.129	-0.346	-0.262	-0.193
$SIMEXP\_D_{it}$	22567	-0.210	0.110	-0.262	-0.192	-0.137
$SIMEXP\_F_{it}$	22722	-0.149	0.109	-0.191	-0.117	-0.075
$SIMEXP2_{it}$	22737	-0.251	0.128	-0.307	-0.225	-0.162
$SIMEXP2\_D_{it}$	22705	-0.186	0.115	-0.232	-0.158	-0.111
$SIMEXP2\_F_{it}$	22737	-0.134	0.099	-0.171	-0.104	-0.068
HI_Cntry_{it}	22737	0.388	0.208	0.230	0.358	0.513
HI_Ind_{it}	22737	0.599	0.262	0.382	0.549	0.850
LFR_{it}	22737	10.324	17.717	0.722	3.348	11.861
ACC_{it}	22737	3.376	1.039	2.773	3.584	4.263
$BOLD_{it}$	22737	0.486	0.190	0.370	0.500	0.610
OPT_{it}	22522	0.505	0.183	0.390	0.500	0.620
$NFIRMS_{it}$	22737	6.788	3.775	4.000	6.000	9.000
$NIND_{it}$	22737	2.654	1.567	1.000	2.000	3.000
$GENEXP_{it}$	22737	5.464	3.729	3.000	4.000	7.000
$BRKSZ_{it}$	22737	43.262	31.234	16.000	36.000	71.000
$FMVR_{it}$	22737	0.142	0.249	0.000	0.000	0.200
$FREQ_{it}$	22737	0.111	1.431	-0.684	0.072	0.841
$LogMV_{it}$	22731	8.258	1.421	7.312	8.301	9.244
IOR_{it}	22737	0.665	0.199	0.571	0.694	0.800

Panel D. Pearson (below the diagonal) and Spearman (above the diagonal) correlation matrix for the individual forecasts sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) A_{jt}		0.20***	0.01***	0.05***	0.17***	0.02***	-0.08***	0.07***	0.03***	0.03***	0.02***	0.03***	0.03***	0.04***	-0.07***	-0.10***
(2) FE_{ijt}	0.34***		0.13***	0.05***	-0.06***	0.04***	-0.01***	0.02***	-0.01***	0.01**	-0.02***	0.00	0.01***	-0.01***	-0.06***	0.01***
(3) $PMAFE_{ijt}$	0.00	-0.00		-0.00	-0.07***	-0.00	0.02***	-0.00	-0.01***	-0.04***	0.01**	-0.00	-0.02***	0.01***	0.01***	-0.03***
(4) CAR_{ijt}	0.07***	0.05***	0.00		0.28***	0.01	-0.00	0.00	0.02***	0.01***	0.01***	0.02***	0.01***	0.02***	0.00	0.01*
(5) $NEWS_{ijt}$	0.29***	-0.06***	-0.09***	0.22***		0.04***	0.04***	-0.00	0.04***	0.01***	0.03***	0.03***	0.01**	0.04***	-0.01**	0.02***
(6) $MACRO_{jt}$	0.02***	0.01**	0.00	-0.00	0.01*		0.43***	0.66***	-0.11***	0.04***	-0.16***	-0.09***	0.03***	-0.15***	-0.16***	0.05***
(7) $MACRO\_D_{jt}$	-0.02***	-0.01**	0.00	-0.01**	0.02***	0.67***		-0.21***	0.25***	-0.07***	0.35***	0.16***	-0.11***	0.35***	0.30***	-0.03***
(8) $MACRO\_F_{jt}$	0.05***	0.02***	-0.00	0.00	-0.01**	0.80***	0.09***		-0.26***	0.06***	-0.36***	-0.15***	0.11***	-0.36***	-0.37***	0.05***
(9) $SIMEXP_{ij,t-1}$	0.07***	0.02***	-0.01***	0.02***	0.04***	-0.09***	0.19***	-0.27***		0.67***	0.76***	0.70***	0.37***	0.73***	0.06***	0.02***
(10) $SIMEXP\_D_{ij,t-1}$	0.05***	0.02***	-0.01***	0.01***	0.01***	0.02***	-0.01	0.03***	0.71***		0.16***	0.41***	0.58***	0.18***	-0.28***	0.13***
(11) $SIMEXP\_F_{ij,t-1}$	0.06***	0.01***	-0.00	0.01***	0.05***	-0.14***	0.26***	-0.40***	0.78***	0.16***		0.57***	0.07***	0.90***	0.33***	-0.04***
(12) $SIMEXP2_{ij,t-1}$	0.07***	0.03***	-0.01**	0.02***	0.04***	-0.07***	0.12***	-0.19***	0.76***	0.50***	0.62***		0.73***	0.64***	0.08***	-0.09***
(13) $SIMEXP2\_D_{ij,t-1}$	0.05***	0.02***	-0.01***	0.01***	0.02***	0.02***	-0.05***	0.07***	0.44***	0.62***	0.09***	0.78***		0.11***	-0.14***	-0.01*
(14) $SIMEXP2\_F_{ij,t-1}$	0.07***	0.02***	-0.00	0.02***	0.05***	-0.13***	0.26***	-0.39***	0.76***	0.19***	0.93***	0.68***	0.12***		0.22***	-0.09***
(15) $HI\_Cntry_{i,t-1}$	-0.06***	-0.04***	-0.01	-0.00	-0.00	-0.07***	0.19***	-0.26***	-0.03***	-0.31***	0.25***	-0.04***	-0.20***	0.16***		-0.05***
(16) $HI\_Ind_{i,t-1}$	-0.07***	0.01***	-0.01***	0.01	-0.00	0.03***	-0.02***	0.07***	0.01***	0.09***	-0.06***	-0.08***	-0.03***	-0.08***	-0.02***	

Table 3. Predicting Firm Earnings with *MACRO*

This table reports the results from OLS regressions of future earnings (A_{jt}) on company-specific fundamental forecast, $MACRO_{jt}$, its components $MACRO\_F_{jt}$ and $MACRO\_D_{jt}$, and control variables. See Appendix I for variable definitions. The *t*-statistics are calculated based on standard errors clustered by firm and year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent variable = A_{jt}	(1)	(2)	(3)	(4)
$MACRO_{jt}$	0.347***		0.212***	
	(3.77)		(2.61)	
$MACRO\_F_{jt}$		0.383***		0.230***
		(3.96)		(2.64)
$MACRO\_D_{jt}$		0.173		0.120
		(1.12)		(0.95)
$Cons_{jt}$			0.422***	0.419***
			(4.79)	(4.73)
$A_{j,t-1}$	0.563***	0.562***	0.279***	0.281***
	(25.67)	(25.54)	(5.19)	(5.23)
$LogMV_{j,t-1}$	0.304***	0.309***	0.322***	0.322***
	(7.14)	(7.22)	(8.41)	(8.40)
$BTM_{j,t-1}$	-1.316***	-1.285***	-1.013***	-1.014***
	(-4.45)	(-4.30)	(-4.16)	(-4.15)
$LOSS_{j,t-1}$	-0.888***	-0.912***	-0.780***	-0.784***
	(-4.42)	(-4.51)	(-4.18)	(-4.15)
$D\_DIV_{j,t-1}$	0.720***	0.684***	0.474***	0.446***
	(5.51)	(5.22)	(3.51)	(3.33)
$DY_{j,t-1}$	-0.019***	-0.019***	-0.019***	-0.019***
	(-2.72)	(-2.70)	(-2.92)	(-2.88)
Industry & Year	Yes	Yes	Yes	Yes
$Adj.R^2$	0.422	0.422	0.556	0.555
N	9843	9726	9843	9726

Table 4. Predicting Consensus Forecast Error with *MACRO*

This table reports the results from OLS regressions of consensus forecast errors, CFE_{jt}, on $MACRO_{jt}$, $MACRO\_F_{jt}$, and components of $MACRO\_F_{jt}$ that incorporate information about a country's economic significance (*Top5* vs *NonTop5*), proximity to the US (*Close5* vs *NonClose5*), analyst coverage (*Cov5* vs *NonCov5*), information precision (*Cntry* vs *Reg*), and total foreign exposure (*HiXps* vs *LoXps*). See Appendix I for variable definitions. The *t*-statistics are calculated based on standard errors clustered by firm and year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var. = CFE_{jt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MACRO_{jt}$	0.169*						
	(1.85)						
β_1 $MACRO\_F_{jt}$		0.202**					
		(2.17)					
γ_1 $MACRO\_F\_Top5_{jt}$			0.135				
			(1.20)				
γ_2 $MACRO\_F\_NonTop5_{jt}$			0.530***				
			(2.78)				
γ_1 $MACRO\_F\_Close5_{jt}$				-0.177			
				(-1.02)			
γ_2 $MACRO\_F\_NonClose5_{jt}$				0.191**			
				(2.19)			
γ_1 $MACRO\_F\_Cov5_{jt}$					0.576		
					(1.45)		
γ_2 $MACRO\_F\_NonCov5_{jt}$					0.194**		
					(2.23)		
γ_1 $MACRO\_F\_Cntry_{jt}$						0.102	
						(1.28)	
γ_2 $MACRO\_F\_Reg_{jt}$						0.267**	
						(2.32)	
γ_1 $MACRO\_F\_HiXps_{jt}$							0.209**
							(2.16)
γ_2 $MACRO\_F\_LoXps_{jt}$							0.393***
							(3.24)
β_2 $MACRO\_D_{jt}$		0.076	0.097	0.068	0.101	0.057	0.021
		(0.61)	(0.63)	(0.59)	(0.87)	(0.47)	(0.16)
$A_{j,t-1}$	0.085***	0.082***	0.083***	0.077***	0.078***	0.083***	0.083***
	(3.57)	(3.45)	(3.33)	(3.32)	(3.33)	(3.67)	(3.47)
$LogMV_{j,t-1}$	0.167***	0.171***	0.161***	0.147***	0.151***	0.166***	0.165***
	(3.47)	(3.62)	(3.95)	(3.22)	(3.30)	(3.79)	(3.48)
$BTM_{j,t-1}$	-2.411***	-2.349***	-2.336***	-2.302***	-2.297***	-2.335***	-2.353***
	(-6.54)	(-6.39)	(-5.66)	(-6.23)	(-6.24)	(-5.81)	(-6.40)
$LOSS_{j,t-1}$	0.357	0.364	0.360	0.322	0.326	0.362	0.361
	(1.55)	(1.56)	(1.62)	(1.40)	(1.40)	(1.50)	(1.56)
$STDROA_{j,t-1}$	-2.795***	-2.800***	-2.648***	-2.779***	-2.716***	-2.641***	-2.751***
	(-3.22)	(-3.31)	(-2.83)	(-3.31)	(-3.18)	(-3.15)	(-3.22)
$LEV_{j,t-1}$	-2.280***	-2.213***	-2.231***	-2.228***	-2.238***	-2.224***	-2.226***
	(-3.94)	(-3.81)	(-4.99)	(-3.93)	(-3.96)	(-4.48)	(-3.85)
$IOR_{j,t-1}$	0.602***	0.701***	0.704***	0.676***	0.682***	0.698***	0.697***
	(2.95)	(3.38)	(2.88)	(3.17)	(3.19)	(3.22)	(3.34)
$ANNRET_{j,t-1}$	0.399***	0.397***	0.403***	0.408***	0.408***	0.404***	0.397***
	(3.18)	(3.11)	(3.97)	(3.12)	(3.11)	(2.83)	(3.11)

$ACCRUAL_{j,t-1}$	0.606*	0.601*	0.603*	0.469	0.465	0.601	0.605*
	(1.74)	(1.73)	(1.65)	(1.43)	(1.42)	(1.63)	(1.74)
$GDPDISP_{jt}$	0.044	0.019	-0.006	-0.071	-0.050	0.007	0.009
	(0.35)	(0.15)	(-0.06)	(-0.88)	(-0.65)	(0.05)	(0.07)
Industry & Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.097	0.096	0.096	0.093	0.093	0.096	0.096
N	8953	8868	8868	8654	8654	8868	8868
Test: $\beta_1 = \beta_2$		2.328					
p-value		(0.132)					
Test: $\gamma_1 = \gamma_2$			5.044	5.554	0.945	3.711	4.765
p-value			(0.025)	(0.019)	(0.332)	(0.055)	(0.030)

Table 5. Predicting Individual Analyst Forecast Errors with *MACRO*

This table reports the results from regressions of individual analyst forecast errors, *FE*, on macroeconomic information, *MACRO*, and *MACRO* interacted with analyst and broker attributes that potentially explain the use of *MACRO*, e.g., *SIMEXP*. See Appendix I for variable definitions. The *t*-statistics are calculated based on standard errors clustered by analyst and year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent variable = FE_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MACRO_{jt}$	0.066***	0.039**	0.009	0.127***			
	(4.53)	(2.19)	(0.41)	(3.13)			
$MACRO_{jt} \times SIMEXP_{ij,t-1}$		-0.149**	-0.139**	-0.141**			
		(-2.41)	(-2.24)	(-2.30)			
$MACRO_{jt} \times HI\_Cntry_{i,t-1}$			-0.012	-0.038			
			(-0.55)	(-1.62)			
$MACRO_{jt} \times HI\_Ind_{i,t-1}$			0.057***	0.009			
			(3.10)	(0.34)			
$MACRO\_F_{jt}$					0.043**	-0.034	0.109**
					(2.12)	(-1.14)	(2.00)
$MACRO\_F_{jt} \times SIMEXP\_F_{ij,t-1}$					-0.243**	-0.242**	-0.240**
					(-2.44)	(-2.37)	(-2.36)
$MACRO\_F_{jt} \times HI\_Cntry_{i,t-1}$						0.024	-0.006
						(0.63)	(-0.16)
$MACRO\_F_{jt} \times HI\_Ind_{i,t-1}$						0.113***	0.051
						(4.51)	(1.56)
$MACRO\_D_{jt}$					0.020	0.043	0.128**
					(0.92)	(1.49)	(2.24)
$MACRO\_D_{jt} \times SIMEXP\_D_{ij,t-1}$					-0.081	-0.059	-0.058
					(-0.93)	(-0.67)	(-0.65)
$MACRO\_D_{jt} \times HI\_Cntry_{i,t-1}$						-0.011	-0.027
						(-0.30)	(-0.73)
$MACRO\_D_{jt} \times HI\_Ind_{i,t-1}$						-0.028	-0.049
						(-1.08)	(-1.28)
$MACRO_{jt} \times LogFIRMEXP_{ijt}$				-0.012**			
				(-1.99)			
$MACRO_{jt} \times LogBRKSZ_{it}$				0.006			
				(1.02)			
$MACRO_{jt} \times LogNFIRMS_{it}$				-0.035***			
				(-2.99)			
$MACRO_{jt} \times LogNIND_{it}$				-0.016			
				(-1.40)			
$MACRO\_F_{jt} \times LogFIRMEXP_{ijt}$							-0.016*
							(-1.90)
$MACRO\_F_{jt} \times LogBRKSZ_{it}$							0.012
							(1.61)
$MACRO\_F_{jt} \times LogNFIRMS_{it}$							-0.045***
							(-2.87)
$MACRO\_F_{jt} \times LogNIND_{it}$							-0.023
							(-1.47)
$MACRO\_D_{jt} \times LogFIRMEXP_{ijt}$							-0.005
							(-0.49)

$MACRO\_D_{jt} \times LogBRKSZ_{it}$							-0.003
							(-0.45)
$MACRO\_D_{jt} \times LogNFIRMS_{it}$							-0.023
							(-1.40)
$MACRO\_D_{jt} \times LogNIND_{it}$							-0.003
							(-0.15)
$SIMEXP_{ij,t-1}$		0.604***	0.565***	0.569***			
		(3.48)	(3.24)	(3.28)			
$SIMEXP\_F_{ij,t-1}$					0.890***	0.876***	0.875***
					(4.51)	(4.44)	(4.45)
$SIMEXP\_D_{ij,t-1}$					0.020	-0.015	-0.019
					(0.17)	(-0.12)	(-0.15)
$HI\_Cntry_{i,t-1}$			-0.025	0.036	-0.105***	-0.119*	-0.061
			(-0.37)	(0.51)	(-2.66)	(-1.72)	(-0.86)
$HI\_Ind_{i,t-1}$			-0.225***	-0.108	-0.087**	-0.214***	-0.106
			(-3.42)	(-1.26)	(-2.32)	(-3.28)	(-1.23)
$LogFIRMEXP_{ijt}$	-0.003	-0.004	-0.008	0.022	-0.010	-0.010	0.018
	(-0.32)	(-0.46)	(-0.99)	(1.22)	(-1.19)	(-1.17)	(0.98)
$LogNFIRMS_{it}$	0.069***	0.060***	0.059***	0.146***	0.060***	0.058***	0.146***
	(4.21)	(3.66)	(3.58)	(4.16)	(3.63)	(3.51)	(4.16)
$LogNIND_{it}$	-0.039**	-0.031*	-0.051**	-0.011	-0.053***	-0.051**	-0.017
	(-2.26)	(-1.78)	(-2.51)	(-0.30)	(-2.63)	(-2.54)	(-0.44)
$LogBRKSZ_{it}$	0.030***	0.030***	0.029***	0.015	0.029***	0.030***	0.017
	(3.87)	(3.82)	(3.75)	(0.92)	(3.74)	(3.83)	(1.04)
$LogHRZN_{it}$	-0.138***	-0.139***	-0.141***	-0.140***	-0.141***	-0.141***	-0.141***
	(-13.45)	(-13.54)	(-13.67)	(-13.66)	(-13.67)	(-13.70)	(-13.74)
$A_{j,t-1}$	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	(4.63)	(4.61)	(4.59)	(4.56)	(4.61)	(4.61)	(4.57)
$STDROA_{j,t-1}$	-0.382***	-0.364**	-0.361**	-0.359**	-0.345**	-0.330**	-0.327**
	(-2.67)	(-2.54)	(-2.52)	(-2.50)	(-2.40)	(-2.29)	(-2.26)
$LogMV_{j,t-1}$	0.028***	0.024***	0.023***	0.023***	0.021***	0.021***	0.021***
	(5.26)	(4.35)	(4.18)	(4.14)	(3.75)	(3.89)	(3.86)
$BTM_{j,t-1}$	-0.299***	-0.300***	-0.306***	-0.310***	-0.301***	-0.300***	-0.303***
	(-5.77)	(-5.81)	(-5.89)	(-5.98)	(-5.83)	(-5.82)	(-5.89)
$LEV_{j,t-1}$	-0.394***	-0.403***	-0.403***	-0.403***	-0.406***	-0.408***	-0.409***
	(-6.13)	(-6.23)	(-6.23)	(-6.24)	(-6.27)	(-6.30)	(-6.32)
$IOR_{j,t-1}$	0.227***	0.222***	0.223***	0.223***	0.226***	0.222***	0.223***
	(7.71)	(7.58)	(7.61)	(7.59)	(6.98)	(6.82)	(6.86)
$LOSS_{j,t-1}$	0.082***	0.080***	0.079**	0.079**	0.079**	0.080**	0.079**
	(2.63)	(2.58)	(2.56)	(2.55)	(2.56)	(2.57)	(2.56)
$ANNRET_{j,t-1}$	0.089***	0.092***	0.092***	0.090***	0.094***	0.095***	0.093***
	(5.33)	(5.44)	(5.46)	(5.34)	(5.53)	(5.58)	(5.49)
$ACCRUAL_{j,t-1}$	-0.080	-0.077	-0.078	-0.078	-0.075	-0.075	-0.076
	(-1.64)	(-1.58)	(-1.60)	(-1.61)	(-1.54)	(-1.55)	(-1.57)
$GDPDISP_{jt}$	0.005	0.003	0.004	0.004	0.006	0.006	0.006
	(0.34)	(0.26)	(0.32)	(0.29)	(0.43)	(0.47)	(0.44)
Industry & Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.056	0.057	0.057	0.057	0.057	0.058	0.058
N	82555	82555	82555	82555	82555	82555	82555

Table 6. Analyst's Global Expertise and Forecast Accuracy

This table reports the results from OLS regressions of analyst forecast accuracy, *PMAFE*, on analysts' global expertise, *SIMEXP* and *SIMEXP_F*, and other accuracy determinants. See Appendix I for variable definitions. The *t*-statistics are calculated based on standard errors clustered by analyst and year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent variable = $PMAFE_{ijt}$	(1)	(2)	(3)	(4)
$SIMEXP_{ij,t-1}$	-0.137***	-0.183***		
	(-2.60)	(-3.53)		
$SIMEXP\_F_{ij,t-1}$			-0.377**	-0.295*
			(-2.44)	(-1.94)
$SIMEXP\_D_{ij,t-1}$			-0.082*	-0.132***
			(-1.68)	(-3.08)
$HI\_Cntry_{i,t-1}$		-0.100***		-0.096***
		(-4.74)		(-5.39)
$HI\_Ind_{i,t-1}$		-0.118***		-0.117***
		(-5.32)		(-5.28)
$LogFIRMEXP_{ijt}$	-0.017***	-0.024***	-0.017***	-0.024***
	(-3.01)	(-4.34)	(-3.02)	(-4.30)
$LogNFIRMS_{it}$	-0.002	-0.003	-0.002	-0.003
	(-0.30)	(-0.38)	(-0.28)	(-0.37)
$LogNIND_{it}$	0.389***	0.387***	0.388***	0.387***
	(18.29)	(18.33)	(18.29)	(18.31)
$LogBRKSZ_{it}$	-0.149***	-0.150***	-0.150***	-0.151***
	(-13.90)	(-13.78)	(-13.66)	(-13.58)
$LogHRZN_{ijt}$	0.042***	0.018	0.042***	0.018
	(3.17)	(1.32)	(3.16)	(1.34)
Constant	-0.086***	-0.086***	-0.085***	-0.086***
	(-22.12)	(-22.13)	(-21.97)	(-22.15)
$Adj.R^2$	0.142	0.143	0.142	0.143
N	82483	82483	82483	82483

Table 7. Global Expertise and Forecast Informativeness

This table reports the results from OLS regressions of the 3-day market reaction to analyst forecast revisions, *CAR*, on forecast news interacted with global expertise: *NEWS* × *SIMEXP* and *NEWS_F*× *SIMEXP_F*. We include but do not tabulate *LogFIRMEXP*, *LogBRKSZ*, *LogNFIRMS*, *LogNIND*, *LogHRZN*, *GDPDISP*, Δ*ROA*, *STDROA*, *LOGMV*, *BTM*, *LEV*, *IOR*, *LOSS*, *ANNRET*, and *ACCRUAL*. See Appendix I for variable definitions. The *t*-statistics are calculated based on standard errors clustered by analyst and year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent variable = CAR_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)
$NEWS_{ijt}$	2.096***	2.444***	1.195***			
	(10.83)	(8.68)	(2.86)			
$NEWS_{ijt}$ × $SIMEXP_{ij,t-1}$	0.765***	0.781***	0.734***			
	(2.80)	(3.11)	(3.14)			
$NEWS_{ijt}$ × $HI\_Cntry_{i,t-1}$		-0.088	0.032			
		(-0.23)	(0.08)			
$NEWS_{ijt}$ × $HI\_Ind_{i,t-1}$		-0.535*	-0.041			
		(-1.73)	(-0.12)			
$NEWS\_F_{ijt}$				2.375***	2.648***	1.659**
				(6.48)	(4.71)	(2.50)
$NEWS\_F_{ijt}$× $SIMEXP\_F_{ij,t-1}$				1.978***	1.733***	1.526***
				(3.87)	(3.42)	(3.02)
$NEWS\_F_{ijt}$× $HI\_Cntry_{i,t-1}$					1.228	0.870
					(1.25)	(0.87)
$NEWS\_F_{ijt}$ × $HI\_Ind_{i,t-1}$					-1.097**	0.287
					(-2.08)	(0.55)
$NEWS\_D_{ijt}$				1.688***	2.193***	0.510
				(6.11)	(4.28)	(0.55)
$NEWS\_D_{ijt}$ × $SIMEXP\_D_{ij,t-1}$				-0.563	-0.034	0.062
				(-0.77)	(-0.04)	(0.08)
$NEWS\_D_{ijt}$ × $HI\_Cntry_{i,t-1}$					-1.865**	-1.124
					(-2.56)	(-1.42)
$NEWS\_D_{ijt}$ × $HI\_Ind_{i,t-1}$					0.395	-0.307
					(0.62)	(-0.48)
$NEWS_{ijt}$ × $LogFIRMEXP_{ijt}$			-0.074			
			(-0.57)			
$NEWS_{ijt}$ × $LogBRKSZ_{it}$			0.061			
			(0.88)			
$NEWS_{ijt}$ × $LogNFIRMS_{it}$			0.255**			
			(2.04)			
$NEWS_{ijt}$ × $LogNIND_{it}$			0.270*			
			(1.74)			
$NEWS\_F_{ijt}$ × $LogFIRMEXP_{ijt}$						0.311
						(1.48)
$NEWS\_F_{ijt}$ × $LogBRKSZ_{it}$						0.053
						(0.40)
$NEWS\_F_{ijt}$ × $LogNFIRMS_{it}$						-0.596*
						(-1.86)
$NEWS\_F_{ijt}$ × $LogNIND_{it}$						1.052***
						(3.42)
$NEWS\_D_{ijt}$ × $LogFIRMEXP_{ijt}$						-0.565*
						(-1.83)

$NEWS\_D_{ijt} \times LogBRKSZ_{it}$						0.084
						(0.54)
$NEWS\_D_{ijt} \times LogNFIRMS_{it}$						1.517***
						(4.16)
$NEWS\_D_{ijt} \times LogNIND_{it}$						-0.921***
						(-3.34)
$SIMEXP_{ij,t-1}$	0.686**	0.689**	0.682**			
	(2.01)	(2.03)	(2.02)			
$SIMEXP\_F_{ij,t-1}$				0.364	0.342	0.305
				(0.55)	(0.52)	(0.46)
$SIMEXP\_D_{ij,t-1}$				0.793*	0.782*	0.785*
				(1.78)	(1.77)	(1.77)
$HI\_Cntry_{i,t-1}$	0.021	0.020	0.037	0.090	0.063	0.085
	(0.08)	(0.08)	(0.15)	(0.30)	(0.21)	(0.29)
$HI\_Ind_{i,t-1}$	-0.067	-0.118	-0.064	-0.081	-0.122	-0.076
	(-0.43)	(-0.76)	(-0.38)	(-0.51)	(-0.77)	(-0.45)
Main effects	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Year	Yes	Yes	Yes	Yes	Yes	Yes
$Adj.R^2$	0.053	0.054	0.054	0.054	0.054	0.056
N	80459	80459	80459	80459	80459	80459

Table 8. All-star Ranking and Global Expertise

This table reports the results from logit regressions of annual all-star ranking, *Star*, and changes in annual ranking, *Star_Up* and *Star_Down*, on analyst's global expertise, *SIMEXP* and *SIMEXP_F*. For each analyst i year t, we calculate the means of $SIMEXP_{ijt}$, $SIMEXP\_F_{ijt}$, $SIMEXP\_D_{ijt}$, $LogMV_{jt}$, and IOR_{jt} across all firms j that analyst i covers in year t as $SIMEXP_{it}$, $SIMEXP\_F_{it}$, $SIMEXP\_D_{it}$, $LogMV_{it}$, and IOR_{it}. See Appendix I for other variable definitions. The t-statistics are calculated based on standard errors clustered by brokerage and year. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Star_{i,t+1}$	$Star\_Up_{i,t+1}$	$Star\_Down_{i,t+1}$	$Star_{i,t+1}$	$Star\_Up_{i,t+1}$	$Star\_Down_{i,t+1}$
$SIMEXP_{it}$	1.015***	0.140	-0.998**			
	(2.88)	(0.33)	(-2.29)			
$SIMEXP\_F_{it}$				1.585***	-0.559	-1.552**
				(2.96)	(-0.92)	(-2.54)
$SIMEXP\_D_{it}$				0.391	0.693	-0.390
				(1.02)	(1.30)	(-0.80)
HI_Cntry_{it}	1.278***	1.197***	-0.749***	1.199***	1.336***	-0.643**
	(6.04)	(4.28)	(-2.88)	(5.42)	(4.75)	(-2.34)
HI_Ind_{it}	-0.610***	-0.512*	0.318	-0.588***	-0.497*	0.300
	(-2.86)	(-1.77)	(1.21)	(-2.76)	(-1.72)	(1.14)
LFR_{it}	-0.003**	0.001	0.003	-0.003**	0.001	0.003
	(-2.11)	(0.28)	(1.05)	(-2.12)	(0.31)	(1.12)
$LogBRKSZ_{it}$	2.142***	2.146***	-0.152*	2.141***	2.151***	-0.144*
	(17.32)	(15.12)	(-1.78)	(17.36)	(15.16)	(-1.68)
ACC_{it}	1.035***	0.884***	-0.703***	1.019***	0.885***	-0.719***
	(6.71)	(3.13)	(-2.59)	(6.58)	(3.12)	(-2.64)
$BOLD_{it}$	0.082	0.041	-0.103	0.102	0.043	-0.112
	(0.54)	(0.15)	(-0.41)	(0.67)	(0.15)	(-0.44)
OPT_{it}	-0.163*	-0.163	0.211	-0.139	-0.158	0.185
	(-1.85)	(-1.08)	(1.49)	(-1.57)	(-1.04)	(1.30)
$LogNFIRMS_{it}$	0.456***	0.421***	0.063	0.451***	0.400***	0.040
	(5.19)	(3.62)	(0.56)	(5.11)	(3.43)	(0.35)
$LogNIND_{it}$	-0.078	-0.118	0.122	-0.092	-0.100	0.143
	(-0.75)	(-0.87)	(0.97)	(-0.87)	(-0.73)	(1.12)
$LogGENEXP_{it}$	0.367***	-0.241***	0.090	0.366***	-0.241***	0.093
	(5.92)	(-2.80)	(1.21)	(5.92)	(-2.80)	(1.24)
$FMVR_{it}$	-0.154	0.417*	0.283	-0.144	0.439**	0.285
	(-1.16)	(1.91)	(1.28)	(-1.08)	(1.99)	(1.29)
$FREQ_{it}$	0.196***	0.135***	-0.108***	0.201***	0.137***	-0.107***
	(7.70)	(3.77)	(-3.63)	(7.84)	(3.79)	(-3.60)
$LogMV_{it}$	0.290***	0.296***	0.072	0.280***	0.302***	0.084*
	(8.65)	(6.54)	(1.64)	(8.47)	(6.72)	(1.92)
IOR_{it}	-0.106	0.389	0.040	-0.219	0.356	0.042
	(-0.54)	(1.40)	(0.14)	(-1.06)	(1.21)	(0.15)
Constant	-14.667***	-15.857***	-1.186*	-14.451***	-15.922***	-1.343*
	(-22.24)	(-17.55)	(-1.65)	(-21.69)	(-17.60)	(-1.85)
$Adj.R^2$	0.270	0.186	0.015	0.271	0.187	0.016
N	22516	19645	2871	22335	19467	2868

Table 9. Alternative Measures of Global Expertise

This table replicates results in Tables 5-8 using an alternative measure of global expertise, *SIMEXP2*. Panel A replicates columns (2) and (5) of Table 5, panel B replicates columns (2) and (4) of Table 6, panel C replicates columns (1) and (4) of Table 7, and panel D replicates Table 8. See Appendix I for variable definitions. The *t*-statistics are calculated based on standard errors clustered by analyst and year (panels A, B, and C) and by brokerage and year (panel C). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A. Individual forecast errors

Dependent variable = FE_{ijt}	(1)	(2)
$MACRO_{jt}$	0.050^{***}	
	(3.20)	
$SIMEXP2_{ij,t-1}$	0.517^{***}	
	(3.64)	
$MACRO_{jt} \times SIMEXP2_{ij,t-1}$	-0.085^{**}	
	(-2.02)	
$MACRO\_F_{jt}$		0.047^{**}
		(2.42)
$SIMEXP2\_F_{ij,t-1}$		1.020^{***}
		(4.77)
$MACRO\_F_{jt} \times SIMEXP2\_F_{ij,t-1}$		-0.178^{**}
		(-2.37)
$MACRO\_D_{jt}$		0.023
		(1.14)
$SIMEXP2\_D_{ij,t-1}$		-0.062
		(-0.62)
$MACRO\_D_{jt} \times SIMEXP2\_D_{ij,t-1}$		0.004
		(0.06)
$HI\_Cntry_{i,t-1}$	-0.050	-0.084^{**}
	(-1.27)	(-2.13)
$HI\_Ind_{i,t-1}$	-0.082^{**}	-0.084^{**}
	(-2.18)	(-2.23)
$LogFIRMEXP_{ijt}$	-0.012	-0.014
	(-1.44)	(-1.61)
$LogNFIRMS_{it}$	0.064^{***}	0.064^{***}
	(3.87)	(3.89)
$LogNIND_{it}$	-0.052^{***}	-0.053^{***}
	(-2.59)	(-2.63)
$LogBRKSZ_{it}$	0.030^{***}	0.030^{***}
	(3.80)	(3.82)
$LogHRZN_{ijt}$	-0.140^{***}	-0.141^{***}
	(-13.65)	(-13.69)
Other controls	Yes	Yes
Industry & Year	Yes	Yes
$Adj.R^2$	0.057	0.057
N	82555	82555

Panel B. Forecast accuracy

Dependent variable = $PMAFE_{ijt}$	(1)	(2)
$SIMEXP2_{ij,t-1}$	-0.148***	
	(-2.70)	
$SIMEXP2\_F_{ij,t-1}$		-0.235**
		(-2.09)
$SIMEXP2\_D_{ij,t-1}$		-0.088
		(-1.39)
$HI\_Cntry_{i,t-1}$	-0.119***	-0.115***
	(-4.13)	(-4.12)
$HI\_Ind_{i,t-1}$	-0.156***	-0.155***
	(-4.93)	(-4.91)
$LogFIRMEXP_{ijt}$	-0.029***	-0.028***
	(-3.45)	(-3.43)
$LogNFIRMS_{it}$	-0.201***	-0.202***
	(-12.69)	(-12.71)
$LogNIND_{it}$	0.024	0.024
	(1.24)	(1.24)
$LogBRKSZ_{it}$	-0.003	-0.003
	(-0.29)	(-0.28)
$LogHRZN_{ijt}$	0.477***	0.477***
	(17.03)	(17.03)
Constant	-0.025***	-0.024***
	(-5.77)	(-5.75)
$Adj.R^2$	0.134	0.134
N	82483	82483

Panel C. Forecast informativeness

Dependent variable = CAR_{ijt}	(1)	(2)
$NEWS_{ijt}$	2.107***	
	(21.49)	
$NEWS_{ijt} \times SIMEXP2_{ij,t-1}$	0.881***	
	(2.96)	
$NEWS\_F_{ijt}$		2.221***
		(9.46)
$NEWS\_F_{ijt} \times SIMEXP2\_F_{ij,t-1}$		1.660***
		(2.68)
$NEWS\_D_{ijt}$		2.013***
		(9.70)
$NEWS\_D_{ijt} \times SIMEXP2\_D_{ij,t-1}$		0.908
		(1.32)
$SIMEXP2_{ij,t-1}$	0.599***	
	(2.82)	
$SIMEXP2\_F_{ij,t-1}$		0.666*
		(1.95)
$SIMEXP2\_D_{ij,t-1}$		0.406*
		(1.85)
$HI\_Cntry_{i,t-1}$	0.118	0.119
	(0.73)	(0.73)
$HI\_Ind_{i,t-1}$	0.055	0.051
	(0.37)	(0.35)
Other controls	Yes	Yes
Industry & Year	Yes	Yes
$Adj.R^2$	0.058	0.058
N	80459	80459

Panel D. All-star ranking

	(1) $Star_{i,t+1}$	(2) $Star\_Up_{i,t+1}$	(3) $Star\_Down_{i,t+1}$	(4) $Star_{i,t+1}$	(5) $Star\_Up_{i,t+1}$	(6) $Star\_Down_{i,t+1}$
$SIMEXP2_{it}$	1.278***	0.731**	-1.488***			
	(5.49)	(2.23)	(-4.28)			
$SIMEXP2\_F_{it}$				1.528***	0.596	-1.267**
				(3.59)	(1.19)	(-2.13)
$SIMEXP2\_D_{it}$				0.744***	0.276	-1.081***
				(3.09)	(1.06)	(-3.22)
HI_Cntry_{it}	1.309***	1.090***	-0.808***	1.261***	1.133***	-0.800***
	(6.76)	(3.26)	(-3.21)	(6.30)	(3.32)	(-3.02)
HI_Ind_{it}	-0.567***	-0.523**	0.277	-0.562***	-0.523**	0.277
	(-2.84)	(-2.38)	(0.91)	(-2.81)	(-2.39)	(0.90)
LFR_{it}	-0.003*	0.001	0.003	-0.003*	0.001	0.003
	(-1.90)	(0.30)	(1.13)	(-1.91)	(0.31)	(1.15)
$LogBRKSZ_{it}$	1.046***	0.799**	-0.704***	1.039***	0.798**	-0.700***
	(5.62)	(2.04)	(-2.98)	(5.52)	(2.04)	(-2.95)
ACC_{it}	0.079	-0.111	-0.095	0.074	-0.116	-0.098
	(0.49)	(-0.54)	(-0.32)	(0.46)	(-0.56)	(-0.33)
$BOLD_{it}$	-0.171	-0.091	0.211	-0.155	-0.095	0.206
	(-1.59)	(-0.45)	(1.61)	(-1.45)	(-0.48)	(1.56)
OPT_{it}	0.403***	0.496***	0.127	0.411***	0.489***	0.115
	(3.65)	(4.64)	(1.18)	(3.74)	(4.58)	(1.06)
$LogNFIRMS_{it}$	-0.064	-0.145	0.108	-0.073	-0.136	0.113
	(-0.61)	(-1.07)	(0.92)	(-0.69)	(-1.00)	(0.96)
$LogNIND_{it}$	0.357***	-0.331***	0.102	0.359***	-0.334***	0.101
	(3.56)	(-3.05)	(1.36)	(3.56)	(-3.07)	(1.33)
$LogGENEXP_{it}$	2.145***	2.088***	-0.153	2.145***	2.090***	-0.154
	(5.36)	(6.42)	(-1.43)	(5.36)	(6.43)	(-1.45)
$FMVR_{it}$	-0.155	0.308	0.303	-0.153	0.318	0.292
	(-1.29)	(1.46)	(1.36)	(-1.27)	(1.52)	(1.32)
$FREQ_{it}$	0.195***	0.174***	-0.111***	0.198***	0.174***	-0.110***
	(4.07)	(3.20)	(-2.95)	(4.09)	(3.21)	(-2.92)
$LogMV_{it}$	0.288***	0.324***	0.081**	0.281***	0.328***	0.082**
	(4.79)	(5.37)	(2.10)	(4.73)	(5.35)	(2.27)
IOR_{it}	-0.184	0.153	0.142	-0.184	0.173	0.118
	(-0.84)	(0.40)	(0.49)	(-0.83)	(0.44)	(0.41)
Constant	-14.519***	-15.542***	-1.503*	-14.437***	-15.598***	-1.467*
	(-8.21)	(-9.18)	(-1.90)	(-8.07)	(-9.14)	(-1.88)
$Adj.R^2$	0.270	0.187	0.017	0.271	0.187	0.017
N	22516	19645	2871	22486	19616	2870