Foreign Direct Investments and Earnings Forecast Accuracy

Abstract:

We investigate the relationship between Foreign Direct Investment (FDI) and the characteristics of earnings forecasts made by both managers and financial analysts. We find that both management earnings forecasts (MEFs) and analyst earnings forecasts (AEFs) made after a larger number of FDI projects undertaken by a firm are less accurate. We also find that this negative relationship is partially mitigated by the firm's managerial ability. This suggests that FDI projects introduce uncertainty about a firm's earnings not just to external market participants, but also to the firm's management. Additional analyses suggest that the negative relationship between FDI forecast accuracy may extend over multiple years. We document that FDI projects are also associated with lower precision MEFs, higher frequency of MEF revisions, and higher dispersion of AEFs. Overall, our results suggest that FDI is an important factor in a firm's information environment and FDI disclosure may be useful to facilitate the decision-making of market participants.

Keywords: management earnings forecasts; analysts' earnings forecasts; foreign direct investment; forecast accuracy; forecast bias; voluntary disclosure; internationalization.

Introduction

This study investigates the relationship between a firm's decision to engage in Foreign Direct Investment (FDI) and the attributes of its earnings forecasts provided by both management and financial analysts. FDI is an instance where a firm injects capital and "obtains a lasting interest in, and a degree of influence over the management, of a business enterprise in another country" (Schwarzenberg, 2022). It marks the initiation or expansion of foreign operations for a firm.

FDI is an important driver of economic growth. According to the United Nations, over two hundred billion dollars flow into developing countries in the form of FDI every year and this amount has remained stable for the four years following 2018 (UNCTAD, 2021). While FDI transfers technology (Chenaf-Nicet and Rougier, 2016) and reduces unemployment (Lipsey, 2001) in the destination market, it is also an important activity in business operations. Multinational firms constitute the majority of the S&P 500 and more than 70% of their revenues came from global sources (Brzenk, 2018). Other than improving profitability, FDI also improves a firm's operational efficiency in global value chains (Moghaddam et al., 2014).

Operationally, FDI often takes the form of capital expenditure projects in foreign countries. Publicly traded firms that undertake such projects often provide press releases announcing these endeavors. FDI can be undertaken to establish a variety of business functions.[1] Due to the nature of FDI, uncertainty is inherent in undertaking FDI projects and arises from various sources such as the motivations and objectives of parties involved, level of expected

[1] Examples of FDI include building new facilities such as factories like GM's electric vehicle factory in Mexico (Wayland, 2021) and operational centers like Ford's global technology and business center in Mexico (Reuters, 2022). FDI projects can also result in specialist facilities like Apple's research and development office in Israel (Marsal, 2015). They can also take the form of capital expenditure projects to upgrade existing overseas facilities such as Tesla's recent upgrade to its Gigafactory in Shanghai (e.g., He,2022; Lambert,2022; Ren,2022).

performance of these parties, and the quality and reliability of these parties involved in the projects (Atkinson et al., 2006). Firms engaging in FDI undertake projects in foreign countries and face additional challenges that exacerbate the uncertainty associated with FDI (when compared to local projects). These challenges include linguistic barriers (Chen et al. 2006), cultural differences (Shenkar, 2001), currency fluctuations (Hitt et al., 2016), and differences in the legislative and bureaucratic environment (Contractor et al., 2021). These challenges make it more difficult to manage foreign or multinational teams and make the outcomes of foreign projects more difficult to predict. For example, FDI projects can cause disruptions to a firm's existing operations, making performance difficult to predict. In July 2022, Tesla suspended most of its production at its Gigafactory in Shanghai for an ambitious upgrade (He, 2022). Suppliers and analysts anticipated increased production capacity (Ren, 2022), in line with Tesla's own expectations, reflected by the automaker reducing the quoted estimated lead-times for orders by Chinese customers (Lambert, 2022). However, the upgrade procedure disrupted the company's production and sales for a period of time following the upgrade. FDI projects may also impact a firm's operations in the future. For instance, Google launched its search engine service in China in 2006 (Sheehan, 2018) to a positive market reception. Although the company was highly ranked by local customers, its engine service was driven out of the Chinese market in 2010 due to local censorship laws and cyber-attacks (Sheehan, 2018).

Stakeholders need earnings information to facilitate their decision-making (Rahman et al., 2019) and form their earnings expectations mainly based on two important information sources: management's forecasts and financial analysts' forecasts (Hutton et al., 2012). The characteristics of Management Earnings Forecasts (MEFs) and Analyst Earnings Forecasts (AEFs) have been documented to be affected by sources of uncertainty. For instance, managers tend to be less likely to issue MEFs during times of high macroeconomic uncertainty and the forecasts issued are more neutral (Kim et al., 2016). Informational uncertainty has been documented to cause AEFs to exhibit a greater degree of error following news events (Zhang 2006). Therefore, we investigate how FDI may affect the characteristics of the management earnings forecasts and analyst earnings forecasts of a firm.

We predict a negative relationship between FDI and earnings forecast accuracy. Based on FDI project information obtained from Bureau van Dijk Orbis Crossborder Investment (BvD Orbis-CI) database, we find that earnings forecasts issued by both managers and analysts are less accurate following FDI projects. We also predict and find that the negative relationship between FDI and earnings forecast (both MEF and AEF) accuracy is mitigated by managerial ability. In addition, we find evidence suggesting that the relationship between FDI and earnings forecast accuracy may persist for multiple years, although the magnitude of the relationship diminishes over time. These results are robust to alternate specifications of FDI based on new project counts as well as project spending, and also to restricting the sample to firms that undertake FDI at least once in our sample period.

In the supplementary analyses, we find that the relationship between FDI and earnings forecast bias is different between MEFs and AEFs, with MEFs (AEFs) being more (less) pessimistic after FDI. For MEFs, our finding is consistent with Godigbe et al. (2022) that managers issue more pessimistic earnings forecasts to prepare for unexpected shocks. For AEFs, our finding is consistent with prior literature that analysts tend to issue less pessimistic forecasts when earnings are less predictable (Lim, 2001; Das et al., 1998; Bradshaw et al. 2016). In line with the negative relation between FDI and earnings forecast accuracy, our results show that when firms undertake a larger number of FDI projects in a fiscal year, managers issue MEFs and

MEF revisions more frequently and the forecasts are less precise. We also find that analyst earnings forecasts exhibit greater dispersion for a firm that undertakes a larger number of FDI projects in a fiscal year.

Our study adds to both the MEF and AEF literature by expanding our understanding of the forecasting behavior of both managers and analysts. Specifically, we examine the characteristics of earnings forecasts issued by managers and analysts following FDI engagements by U.S. public companies. Prior literature examines the relationship between operating activities and forecast attributes from both management and analyst sides (e.g., Godigbe et al. 2022; Duru & Reeb 2002). Our study expands on extant literature by investigating the role of investing activities (i.e., FDI) in earnings forecasts. Our findings provide insight to companies that have already engaged or intend to engage in investing activities directly in foreign countries. We document how FDI projects can affect a firm's information environment and showcase how these changes may manifest in terms of MEF and AEF characteristics. Our findings suggest that FDI projects can affect the disclosure behavior of managers and analysts and, therefore, it may be beneficial for regulators to consider enhancing FDI information disclosure to facilitate the decision-making of market participants.

Literature Review and Theoretical Development

Foreign Direct Investment

Prior management and international business literature explain FDI decisions from different perspectives. Dunning's (2008) OLI paradigm explains FDI behavior from three aspects: ownership, resource-based advantages, and locational characteristics of the foreign nation. Other than the OLI paradigm, Institutional Theory (North, 1990) and Transactions Cost

Economics theory (Williamson, 2010) are also used in the literature to explain FDI decisions. In general, companies engaging in FDI seek to achieve cost reduction and efficiency in global value chains (Moghaddam et al., 2014). Specific factors documented to influence FDI decisions include host-country contract enforcement and international trade regulations (Contractor et al., 2021), host-country culture and norms (Contractor et al., 2021), home-country attributes (Cui & He, 2017), and managerial ethnic ties (Jean et al., 2011).

The relation between FDI and firm performance is not monotonic (Riahi-Belkaoui, 1998; Capar & Kotabe, 2003; Lu & Beamish, 2004). The performance impact of FDI depends on various factors (e.g., Doukas & Lang, 2003; Lu & Beamish, 2004; Chang & Rhee, 2011). For instance, Doukas and Lang (2003) document that only core-related FDI improves long-term performance and, compared with single-segment firms, multi-segment firms benefit more from core-related FDI. Using Korean sample firms, Chang and Rhee (2011) find that firms making rapid FDI expansion are more profitable if they have superior internal resources and capabilities, or if they are in industries with high globalization pressures. Lu and Beamish (2004) document an S-shaped relation between FDI and firm performance and document that firms perform better if they invest more in intangible assets.

Earnings Forecasts

The usefulness of earnings information has been discussed extensively in prior accounting literature (Ball & Brown, 1968; Beaver, 1968; Lev, 1989). Stakeholders, such as owners, creditors, management, and potential investors all need earnings information to facilitate their decision-making (Rehman et al., 2019). Investors form their earnings expectations mainly based on two important information sources: management's forecasts and financial analysts' forecasts (Hutton et al., 2012).

Management earnings forecasts are voluntary disclosures that affect the behavior of market participants (Hirst et al., 2008). Managers are insiders who make important business decisions and are familiar with business operations. Beyer et al. (2010) show that management earnings forecasts are the most influential factor that impacts accounting-based stock returns. Managers issue earnings forecasts when market participants demand such information for valuation purposes (Hirst et al., 2008). Specifically, firms with higher information asymmetry are more likely to issue management earnings forecasts (Coller and Yohn, 1997), while firms with higher information uncertainty provide management earnings forecasts more frequently (Guay et al., 2016). However, the informativeness of earnings guidance depends on information acquisition costs (Godigbe et al., 2022) and managerial ability (Baik et al., 2011).

Another important source to obtain information about future earnings is financial analysts. Acting as capital market information intermediaries, financial analysts incorporate important information that requires certain expertise to process (Hutton et al., 2012). Specifically, financial analysts generate earnings forecasts and stock recommendations based on accessible macroeconomic, industry, and firm-specific information (Hutton et al., 2012; Boni & Womack, 2006; Clement, 1999). Prior literature investigating analysts' forecasting behavior mainly focuses on attributes such as following decisions, forecast frequency, accuracy, and bias. The accuracy of earnings forecasts is important as it not only affects analysts' career outcomes but also influences market prices and researchers' inferences (Groysberg et al., 2011; Kothari et al., 2016). According to Groysberg et al. (2011), analyst forecast accuracy is one of the most studied measures used to assess analyst performance. Kothari et al. (2016) summarize in their review study that analyst forecast accuracy is largely affected by firm-level attributes such as firm complexity, volatility, and performance transitory.

FDI and Earnings Forecasts

Following Schwarzenberg (2022), we define FDI as a firm's capital injection into a foreign country. In other words, a firm's FDI engagements establish the commencement or expansion of its foreign operations. Therefore, FDI may cause issues that a firm seldom encounters in domestic settings, inducing uncertainties and challenges that complicate the firm's information environment. Initiating new operations in foreign countries magnifies operational complexity (Duru & Reeb, 2002), coordination difficulties, information asymmetry, and incentive misalignment between headquarters and local management (Lu and Beamish, 2004). The geographic and cultural differences between home and host countries also increase information costs (Godigbe et al., 2022). Companies operating abroad face linguistic barriers and cultural differences, leading to communication difficulties (Chen et al., 2006; Alderfer and Smith, 1982). The costs associated with predicting future earnings of firms engaging FDI are driven by two forces: (1) uncertainty and complexity raised from new operations overseas and (2) uncertainty and complexity raised from geographic diversification and distance.

First, a firm may undertake FDI projects in order to set up their foreign operations that allow them to carry out a variety of business functions (e.g., retail and sales offices, manufacturing, business services, and R&D centers). Although existing segment reporting to some degree provides information about a firm's exposure to foreign operations, they capture neither capital flows nor the initiation or expansion of foreign operations.[2] Foreign operations

[2] The SEC requires publicly traded firms to separately disclose revenues from "external customers attributed to an individual foreign country (if these revenues) are material" (17 CFR 229; ASC 280-10-50-4).

increase a firm's fundamental uncertainty by complicating its operating environment (Duru & Reeb, 2002). Starting new foreign operations induces unanticipated situations, such as exchange rate fluctuations, institutional risks, and agency problems (Hitt et al., 2006). These factors make it difficult to assess the effects of FDI projects on business operations in general, adding a layer of complexity to the prediction of future performance. These factors may also explain why prior FDI literature report mixed findings in the relationship between FDI and performance (Riahi-Belkaoui, 1998; Capar and Kotabe, 2003; Lu and Beamish, 2004). In addition, prior literature documents that international diversification increases earnings volatility (Goldberg and Heflin, 1995; Reeb et al., 1998), making earnings forecasts challenging (Waymire, 1985; Duru & Reeb, 2002).[3]

Second, geographical and cultural differences are important aspects of FDI engagements. Firms undertaking FDI projects in different foreign countries constantly interact with locals who work with different cultural expectations, social norms, languages, and standards. Therefore, compared with domestic collaborations, FDI activities increase information asymmetry (Lu & Beamish, 2004), and it is more costly to acquire and process information about business activities overseas (Godigbe et al., 2022). Other than geographic diversification, geographic distance also contributes to the increasing information cost associated with FDI engagements. Prior literature finds evidence that geographic proximity facilitates the acquisition of "soft" information (Ghoul et al., 2013; Agarwal, S. and Hauswald, R., 2010). Therefore, relative to domestic investments, FDI increases the information costs for future earnings.

[3] FDI differs from internationalization captured by prior accounting literature in two ways. First, FDI projects represent the initiation or expansion of overseas operations contrasting with activities revealed by segment reporting. Second, foreign investments in countries that do not directly generate revenue or material levels of revenue are captured by FDI, but not by existing segment disclosures.

Based on the above, we predict that the fundamental uncertainty and information uncertainty associated with FDI activities increase the difficulty of collecting and processing information to forecast future earnings. We expect this increased difficulty to be reflected in the accuracy of earnings forecasts provided by management and financial analysts. We formally state our hypotheses below:

H1a: Management Earnings Forecasts issued after FDI projects are less accurate.

H1b: Analyst Earnings Forecasts issued after FDI projects are less accurate.

To further investigate the association between FDI and earnings forecast accuracy, we next examine the role of management in this relationship. Prior literature shows that the ability of top management plays an important part in increasing shareholder and creditor wealth (Anggraini and Sholihin, 2021; Park et al., 2016; Yung and Chen, 2018). Managerial ability has been documented to enhance firms' information environment (Baik et al., 2018) through several mechanisms, such as better earnings quality (Demerjian et al., 2013), higher likelihood of income smoothing (Demerjian et a., 2017), and more frequent earnings guidance with higher quality (Baik et al., 2011).

Managers with better ability should be able to better handle the additional uncertainty and complexity that FDI engagements add to their firm's information environment. Therefore, ceteris paribus, we expect that managerial ability can to some extent mitigate the negative association between FDI and forecast accuracy. Firms with more capable managers also have better information environments and analysts who follow such firms are also more likely to receive higher-quality information (Baik et al., 2018). We predict that the reduction in forecast accuracy associated with FDI is less pronounced for firms with managers of higher ability. We formally state our hypotheses below:

H2a: The negative relationship between FDI and Management Earnings Forecast accuracy is weaker for firms with high ability managers.

H2b: The negative relationship between FDI and Analyst Earnings Forecast accuracy is weaker for firms with high ability managers.

Empirical Design and Tests

Empirical Models

For our investigation of H1a, we utilize the following multivariate regression model at the management forecast level:

$$MEF\_Accuracy = \beta_0 + \beta_1 FDI + \gamma_0 Controls + \gamma_1 Industry + \gamma_2 Year + \varepsilon \quad (1)$$

where *MEF_Accuracy,* the dependent variable of interest, is the unsigned difference between management forecasted EPS and actual EPS, scaled by stock price at the beginning of a fiscal year and multiplied by -100. If a MEF is given as a range, the upper bound of the MEF is used for the calculation of *MEF_Accuracy.*[4] This operation is consistent with Ciconte et al., (2014) in which the authors document that the upper bound of a range forecast captures market participants' interpretation of the forecast more than the midpoint. *FDI,* the independent variable of interest, is the natural logarithm of one plus the number of FDI projects reported by a firm during 365 days prior to each one of its management earnings forecasts. *Industry* and *Year* represent industry (2 digit sic codes) and year fixed effects respectively.

Controls is a matrix of control variables related to MEF characteristics. The control variables that we utilize for our MEF level regressions are as follows. We include firm characteristics such as size (*Size*) market to book (*MTB*), and earnings volatility (*EarnVol*) which

[4] Managers can provide a range EPS forecast where they provide an upper and lower bound for their EPS prediction, or a point forecast where they provide just a single number for their EPS prediction.

are documented by prior research to be related to forecast accuracy (e.g., Baginiski et al., 2022). Accruals quality (*AccQuality)* is included because accruals are associated with earnings forecast error (Gong et al., 2009). Analyst following (*AFollow)* is included as analyst following is reflective of the information environment of the firm (Frankel and Li, 2004). Board independence (*BoardInd*) is included because firm governance and board characteristics are associated with management forecast characteristics (Karamanou and Vafeas, 2005). Because FDI is a form of capital expenditure, we also include capital expenditures (*Capex*) as a control in order to disentangle the effects of FDI from that of other types of capital expenditures. We control for the horizon of the management earnings forecast (*MEF_Horizon*) because we expect that longer-horizon forecasts are more difficult to predict. We include industry concentration (*IndustryConc*) and litigation risk (*LitRisk*) as they are related to a firm's disclosure costs (Yang 2012). Institutional ownership (*InstOwn*) is included because firms with higher institutional ownership provide more accurate, more frequent, and less optimistic forecasts (Ajinkya et al., 2005). We also control for accounting reporting complexity (*AccComplexity*). Manager ability (*Ability*) is included to control for its effect on forecasting attributes (Baik et al., 2011). To control for the effect of internationalization on MEF documented in the prior literature (Smith et al., 2007; Godigbe et al., 2022), we include the number of international segments reported by a firm (*GeoSegs*). We also include an indicator for loss predictions (*PredictLoss*) because forecasting behavior may be different when management anticipates losses. We utilize robust standard errors clustered at the firm level in our analyses. Detailed information regarding the construction of all variables used is provided in Appendix A.

In the supplementary analyses, the dependent variable of interest for our MEF level regressions is replaced by one of the following attributes: *MEF_Bias* and *MEF_Horizon.*

MEF_Bias is the difference between management forecasted EPS and actual EPS scaled by the stock price at the beginning of the fiscal year and multiplied by 100. If a MEF is given as a range, the upper bound of the MEF is used for the calculation of *MEF_Bias*. *MEF_Horizon* is the natural logarithm of the number of days between an MEF and the end of the fiscal year.

Similarly, for our investigation of H1b, we utilize the following multivariate regression model at the analyst forecast level:

$$AEF\_Accuracy = \beta_0 + \beta_1 FDI + \gamma_0 Controls + \gamma_1 Industry + \gamma_2 Year + \varepsilon \quad (2)$$

where *AEF_Accuracy* is the dependent variable of interest, *FDI* is the independent variable of interest, and *Controls* is a matrix of control variables related to AEF characteristics. *Industry* and *Year* are industry (2 digit sic codes) and year fixed effects respectively. *AEF_Accuracy* is the unsigned difference between analyst forecasted EPS and actual EPS of a fiscal year, scaled by the firm's stock price at the beginning of the fiscal year, multiplied by -100. We include the following control variables in our AEF analysis. We include the following control variables as previously defined: firm size (*Size*), market to book (*MTB*), earnings volatility (*EarnVol*), accruals quality, (*AccQuality)*, analyst following,(*AFollow),* board independence (*BoardInd*), capital expenditures (*Capex*), industry concentration (*IndustryConc*), litigation risk (*LitRisk*), Institutional ownership (*InstOwn*), reporting complexity (AccComplexity), manager ability (*Ability*), and international segments reported by a firm (*GeoSegs*). In addition, we also include the horizon of the analyst forecast (*AEF_Horizon*) because earnings forecasts with greater temporal distance are expected to be less accurate. We include an indicator for whether or not a firm reports foreign operations. (*ForOp*) to control for potential differences in the firm's information environment due to internationalization. We also include firm leverage (*Leverage*) since it can influence certain characteristics of analyst forecasts (Avramov et al., 2009). In addition, we include the following audit-related control variables, an indicator for firms hiring a

"Big 4" auditor (*Big4*), auditor tenure (*AuditorTenure*), the importance of the firm as a client of their auditor (*AuditImportance*), and total audit fees (*AuditFees*) because characteristics of the audit-client relationship have been documented to affect a firm's information environment (e.g., DeFranco et al., 2011; Francis et al., 2019). We also control for *EarnChange*, the change in net income from the previous fiscal year, because analyst earnings forecasts may be more difficult when there is a drastic change. Lastly, we also include an indicator for whether or not a firm announces a merger in that fiscal year (*Merger*) and an indicator for whether or not a firm reports a loss in that year (*Loss*). Following prior analyst forecast literature (e.g., Francis et al., 2019), we utilize robust standard errors clustered at the analyst level in our regressions.

For our investigation of H2a, we construct an indicator variable, *TopAbility*, that equals 1 when an earnings forecast is for a firm with top quintile managerial ability and 0 if the firm's managerial ability falls in the bottom quintile in a given year. We interact this indicator with *FDI* and all controls used in *Model (1)* in the following manner:

$$MEF\_Accuracy = \beta_0 + \beta_1 FDI + \beta_2 TopAbility + \beta_3 (TopAbility * FDI) + \gamma_0 Controls + \gamma_1 (TopAbility * Controls) + \gamma_2 Industry + \gamma_3 Year + \varepsilon \tag{3}$$

Similarly, for our investigation of H2b, we use the same indicator variable, *TopAbility*, to interact with FDI and all control variables used in *Model (2)*.

$$AEF\_Accuracy = \beta_0 + \beta_1 FDI + \beta_2 TopAbility + \beta_3 (TopAbility * FDI) + \gamma_0 Controls + \gamma_1 (TopAbility * Controls) + \gamma_2 Industry + \gamma_3 Year + \varepsilon \tag{4}$$

Detailed information regarding the construction of all variables used is provided in Appendix A.

Sample Information and Descriptive Statistics

We utilize the following datasets to assemble our sample: the Bureau van Dijk Orbis Crossborder Investment (BvD Orbis-CI) database for FDI data, I/B/E/S for forecast-related dependent variables and control variables, Compustat for controls based on firm fundamentals, Audit Analytics for audit-related controls, Boardex for board-related controls, Thompson Reuter's 13f database to calculate our institutional ownership control variable, the updated managerial ability score dataset (Dermejian et al., 2012) provided publicly by Peter Dermejian[5] for our managerial ability control variable as well as the accounting reporting complexity dataset (Hoitash and Hoitash, 2022) provided publicly by Udi Hoitash and Rani Hoitash[6] for our complexity control variable.

Our FDI data is drawn from the BvD Orbis-CI database. Orbis database is the most frequently used microdata source and has been examined for its robustness in relation to other data sources including the United Nation Conference of Trade and Development (UNCTAD) and the World Bank. Orbis-CI gathers a wide range of information, for example, industry segments, project types, project deals (mergers, acquisitions, joint ventures), date of investment, the location of the foreign investors, and the home country of investing firms. Orbis-CI identifies new projects (also known as greenfield FDI) at the firm level and relevant information is collected daily, allowing us to count the total number of FDI projects for each firm in a given period of time.[7] To match with the other firm-level variables while avoiding missing

[5] Available at https://peterdemerjian.weebly.com/managerialability.html.
[6] Available at https://www.xbrlresearch.com/.
[7] Orbis collects information on FDI from a variety of sources, including company reports, government records, and industry publications. There are various ways in which firms disclose information about their foreign direct investment (FDI) activities. One way is through publicly available financial statements and reports, such as annual reports, 10-Ks, and 10-Qs, which are required to be filed with regulatory agencies such as the Securities and Exchange Commission (SEC) in the United States. These documents typically include information about a company's FDI activities, such as the number of FDI made, the countries in which the FDI was made, and the purposes for which the FDI was made. In addition to financial statements and reports, firms may also disclose

observations, we employ both names (including investing company name and Global Ultimate Owner name) and tickers as identifiers for firms in the merge. We restrict our sample to observations from fiscal years 2013 through 2020. This timeframe for our sample is constrained by the availability of data. Our FDI data begins in 2013 and our managerial ability data ends in 2020. Therefore, This procedure leaves 31,490 (4,104,353) unique MEFs (AEFs).

<Table 1>

Table 1 reports the details with regards to sample selection and the breakdown of our MEF sample in terms of industry and fiscal years. For the MEF level sample utilized for most of our MEF analyses, we begin with 31,490 annual MEFs provided in the I/B/E/S Guidance Detail file and retain only annual Earnings Per Share (EPS) forecasts for fiscal year 2013 through 2020 and exclude 411 pre-announcements (MEFs released after the end of the fiscal year) following Bagniski et al. (2022). We then retain only observations with all the required control variables for our estimation of *Model (1)*, resulting in a final sample of 14,992 observations (Table 1 Panel A). Table 1 Panel B shows the breakdown of our sample by industry (2 digit SIC code) and Table 1 Panel C shows the breakdown of our sample by fiscal year.

<Table 2>

Table 2 reports the details with regards to sample selection and the breakdown of our AEF sample in terms of industry and fiscal years. For the AEF level sample utilized for most of our AEF analyses, we begin with 114,284 analyst forecasts provided in the I/B/E/S Detail file and retain only annual EPS forecasts for fiscal years 2013 through 2020. We then eliminate

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information about their FDI activities through press releases, conference calls, and other public communications. Many countries also have specific reporting requirements for FDI, which may require companies to disclose certain information about their FDI activities to government agencies or other regulatory bodies. Finally, firms may also disclose information about their FDI activities through their websites and other online platforms, such as social media. This can be a useful way for companies to share information about their FDI activities with a wide audience, including investors, customers, and other stakeholders.

104,724 forecasts that are released after the end of the fiscal year to be consistent with our treatment of MEFs and retain only the last forecast per analyst-firm-year (similar to Baik et al. 2011). We then retain observations with all the required control variables built for our estimation of *Model (2)*. We end up with a final sample of 114,284 observations (Table 2 Panel A). Similar to our MEF sample, most of the AEF observations are also from manufacturing and services industries (Table 2 Panel B). Table 1 Panel B shows the breakdown of our sample by industry (2 digit SIC code) and Table 1 Panel C shows the breakdown of our sample by fiscal year.

<Table 3>

Table 3 presents the descriptive statistics for variables used for MEF analyses and AEF analyses in panels A and B, respectively. The two sets of analyses are based on sample firms with comparable fundamentals.

Empirical Results

FDI and Earnings Forecast Accuracy

The results of our main MEF analyses utilizing *Model (1)* for the investigation of H1a are presented in Table 4 Panel A. Column (1) reports the results of the MEF analysis utilizing the full sample. The coefficient for FDI in column (1) is significant and negative (-0.162, t = -3.83), indicating that MEF accuracy is negatively related to the number of FDI projects announced prior to the MEF. Specifically, every 1% increase in the number of FDI projects is associated with a 0.162 decrease in MEF accuracy, equivalent to a 5.7% decrease relative to its mean (-0.057= [-0.162×0.571]/1.626). There may be a concern that certain firm characteristics may drive both the decision to undertake FDI as well as MEF accuracy. Therefore, we repeat our analysis in Column (1) using a subsample consisting solely of firms that undertake at least 1 foreign investment project (henceforth referred to as FDI-engaging Firms) in our sample period (2013 - 2021). The result of this analysis is presented in Column (2). The coefficient of FDI remains significantly negative (-0.145, t = -3.58). Taken together, these results provide support for H1a and suggest that the uncertainty of FDI contributes to the lower MEF accuracy that we observe in our analyses.

<Table 4>

The results of our main AEF analyses utilizing *Model (2)* for the investigation of H1b are presented in Table 4 Panel B. Column (1) reports the results of the AEF analysis utilizing the full sample. The coefficient for FDI is negative and significant (-0.944, t = -14.70), indicating that a larger number of FDI within 365 days prior to analyst forecasts is associated with less accurate analyst forecasts. In other words, every 1% increase in the number of FDI projects is associated with a 0.944 decrease in AEF accuracy, equivalent to a 4.7% decrease relative to its mean (-0.047= [-0.944×0.580]/11.735). We then repeat the analysis in Column (1) using a subsample consisting solely of FDI-engaging firms and report the results in Column (2). The coefficient for FDI is negative and significant as well (-0.331, t = -5.93). These results and provide support for H1b and are consistent with the results for the previous MEF analyses.

The Effect of Managerial Ability on FDI - Forecast Accuracy Relationship

To investigate H2a, which examines the effect of managerial ability on the relationship between FDI and MEF accuracy, we utilize a modified version of *Model (1)* where we interact *TopAbility* with *FDI* as well as all control variables utilized in *Model (1)*. The results are reported in Table 5 Panel A. The full sample results are reported in column (1) while the results for FDI-engaging firms are reported in column (2). The coefficient for FDI remains negative and significant in both columns (1) (-0.292, t = -2.61) and (2) (-0.238, t = -2.48). The coefficient for the interaction between *FDI* and *TopAbility* is positive and significant in both columns (1) (0.273, t = 2.04) and (2) (0.249, t = 2.20). These results suggest that while a larger number of FDI is associated with less accurate MEFs, managerial ability mitigates this negative relationship. Overall, these results are consistent with our prediction in H2a.

<Table 5>

Similarly, we utilize a modified version of *Model (2)* where we interact *TopAbility* with *FDI* as well as all control variables utilized in *Model (2)* to investigate the effect that managerial ability has on the relationship between FDI and AEF accuracy (H2b). The results are reported in Table 5 Panel B. The full sample results are reported in column (1) while the results for FDI-engaging firms are reported in column (2). The coefficient for FDI remains negative and significant in both columns (1) (-2.094, t = -10.78) and (2) (-0.887, t = -5.48). The coefficient for the interaction between *FDI* and *TopAbility* is positive and significant in both columns (1) (1.498, t = 7.45) and (2) (0.832, t = 5.06). These results are consistent with H2b that managerial ability acts as a moderator that mitigates the negative relationship between FDI and AEF accuracy.

Robustness and Additional Analysis

Alternative windows of FDI effect

Previously, we utilized the natural log of one plus the number of FDI projects reported during the 365 days prior to MEF / AEF in our main analyses. To gain further insight regarding the impact of FDI on earnings forecasts, we also undertake the regressions in *Model (1)* and Model *(2)* using alternative windows.

<Table 6>

The results of these MEF regressions are reported in Tables 6 Panel A. The results for the AEF regressions are reported in Table 6 Panel B. In column (1) of Table 6 Panel A (Panel B), *FDI_90* is the natural logarithm of one plus the number of FDI projects announced during the 90-day period prior to the MEF (AEF); In column (2), *FDI_365* is the natural logarithm of one plus the number of FDI projects announced during the 365-day period prior to the MEF (AEF) – this is the same as the previous definition of *FDI* used in our main regressions. Similarly, *FDI_730* in column (3) and *FDI_1095* in column (4) are defined as the natural logarithm of one plus the number of FDI projects reported during the 730- and 1095-day periods prior to a MEF (AEF), respectively. Interestingly, while the coefficients are all significantly negative across the board, the magnitude of the impact of FDI on both MEF and AEF accuracy is the strongest for *FDI_90* and becomes weaker for longer window specifications. These results are consistent with a situation where the uncertainty with FDI projects is the highest at the beginning of the engagements and uncertainty gets resolved as progress is made on the projects. One possible concern with these long windows is that the relationship between FDI and forecast accuracy may simply be driven solely by the projects that are reported closer to the forecast dates. To address this concern, we also tested two distinct measurement windows that capture FDI projects between 366 and 730 days prior to the forecasts as well as between 731 and 1095 days prior to the forecasts. Untabulated results of these analyses also yield significant coefficients with similar inferences. Taken together, these results suggest that the effect that FDI has on earnings forecasts can be far-reaching, extending across multiple reporting periods.

Alternative specifications of FDI

We run our main analyses with two alternative specifications of *FDI*: *FDI_New* and *FDI_Spending*. *FDI_New* is the natural logarithm of one plus the number of New FDI projects within 365 days prior to the earnings forecast.[8] *FDI_Spending* is the natural logarithm of the number of millions of dollars spent on foreign projects within 365 days prior to the earnings forecast. The results of the MEF analyses utilizing alternative specifications of *FDI* are presented in Table 7 Panel A. Column (1) reports the results for the regression for *FDI_New* using the full sample while column (2) reports the results for the regression for *FDI_New* using the sample consisting of FDI-engaging firms. The coefficient for *FDI_New* is significantly negative in both column (1) (-0.181, t = -3.45) and column (2) (-0.171, t = -3.45). The coefficients for *FDI_Spending* reported in Column (3) (-0.045, t = -3.79) and Column (4) (-0.034, t = -3.08) are negative and significant as well. In other words, every 1% increase in the amount spent on FDI projects corresponds to a 5.2% (5.1%) decrease in MEF accuracy relative to its mean (-0.052= [-0.181×0.471]/1.624; -0.051= [-0.045×1.840]/1.624).

<Table 7>

The results of AEF analyses utilizing alternative specifications of FDI are presented in Table 7 Panel B. Column (1) reports the results for the regression for *FDI_New* using the full sample while column (2) reports the results for the regression for *FDI_New* using the sample consisting of FDI-engaging firms. The coefficient for *FDI_New* is significantly negative in both column (1) (-0.965, t = -13.89) and column (2) (-0.342, t = -5.76). The coefficients for *FDI_Spending* reported in Column (3) (-0.254, t = -13.49) and Column (4) (-0.094, t = -5.30) are

[8] FDI projects can be classified into 'New' - new projects not related to or located with existing projects, 'Expansion' - expansion of existing foreign operations, 'Co-Location' – a new project that is located with an existing foreign operation, and 'Relocation' - the relocation of existing local / foreign operations overseas.

also negative and significant. Every 1% increase in the number of new FDI projects (FDI spendings) corresponds to a 4.0% (3.9%) decrease in MEF accuracy relative to its mean (-0.040= [-0.965×0.491]/11.735; -0.039= [-0.254×1.805]/11.735). Taken together, the results in Table 7 suggest that new FDI projects and FDI projects of larger scale are negatively associated with both MEF and AEF accuracy. The results presented in Table 7 provide support that the results previously documented in Table 4 are robust to these alternate specifications of *FDI* and that the effect that new FDI projects have on earnings forecast accuracy is not significantly different from the impact of other types of FDI projects.

FDI and Earnings Forecast Bias

In this section, we investigate the relationship between *FDI* and earnings forecast bias. Extant literature documents that analysts may issue forecasts optimistically in order to be able to get more information from managers (Lim, 2001). On the other hand, extant MEF literature indicates that managers tend to provide more pessimistic earnings forecasts in face of uncertainty to avoid potential litigation risk and to reduce the likelihood of missing predicted earnings (Godigbe et al., 2022).

<Table 8>

The results are tabulated in Table 8. Column (1) reports the results for MEF Bias with the full sample and Column (2) reports the results for MEF Bias with the sample consisting only of FDI-engaging firms; Column (3) reports the results for AEF Bias with the full sample and Column (4) reports the results for AEF Bias with the sample consisting only of FDI-engaging firms. The coefficients for *FDI* for the MEF regressions are consistently negative and significant in both columns (1) and (2) (-0.162, t = -3.83; -0.145, t = -3.58) indicating that management forecasts tend to provide less optimistic forecasts following more FDI activities. In contrast, the coefficients for *FDI* for AEF regressions are consistently positive and significant in both columns (3) and (4) (0.398, t = 11.94; 0.202, t = 6.97) indicating that analysts issue earnings forecasts more optimistically following higher numbers of FDI projects. These findings are consistent with prior literature that analysts issue optimistically biased forecasts when forecasting difficulty is high (e.g., Ackert and Athanassakos, 1997; Bradshwa et al., 2016). Taken together, these results provide further support for a scenario where FDI induces greater forecasting uncertainty, making earnings forecasts more difficult for both managers and analysts, leading managers (analysts) to issue more (less) pessimistic forecasts.

FDI and Earnings Forecast Horizon

When managers face uncertainty, they may choose to delay their forecasts (Kim et al., 2016). We expect that the same should apply to analysts as well. To investigate the relationship that FDI has with MEF (AEF) horizon, we use a modified version of *Model (1)* (*Model (2)*) where *MEF_Horizon* (*AEF_Horizon*) is the dependent variable instead of a control variable.

<Table 9>

Results are tabulated in Table 9. The coefficients for *FDI* in Table 9 Column (1) (-0.044, t = -3.04) and Column (2) (-0.55, t = -3.39) are negative and significant, indicating that MEFs issued after a larger number of FDI have shorter horizons. Similarly, the coefficients for *FDI* in Table 9 Column (3) (-0.094, t = -8.04) and Column (4) (-0.133, t = -10.40) are negative and significant, indicating that AEFs issued after a larger number of FDI have shorter horizons as well. Based on these results, it is plausible that both managers and analysts are conscious of the increased forecasting uncertainty due to FDI and delay issuing forecasts until they are more certain.

FDI and MEF Precision, Frequency, and Revisions

Uncertainty regarding recently undertaken FDI projects may cause managers to issue less precise earnings forecasts, plausibly in order to mitigate litigation risk. In addition, as a result of reduced forecast accuracy, managers may choose to issue more forecasts / forecast revisions. In order to investigate this phenomenon, we undertake three different sets of regressions utilizing modified versions of *Model (1)* where the dependent variables are: *Precision,* the average difference between the top and bottom bounds of a management earnings forecast, scaled by the lower bound, then multiplied by -1 and 0 for point forecasts, *Frequency,* the natural logarithm of one plus the number of annual earnings MEFs issued by a firm in a fiscal year, and *Revisions,* the natural logarithm of one plus the number of MEF forecast revisions (annual earnings MEFs after the first one) issued by a firm in a fiscal year. We run these regressions at the firm-year level rather than the forecast level[9] and replace *FDI* with *FDI_Fyend*[10], the natural log of one plus the number of FDI projects reported within 365 days from the current fiscal year end. The results of these regressions are reported in Table 10.

<Table 10>

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[9] We utilize a firm-level level analysis because *Frequency* and *ProbIssue* cannot be tested at the forecast level and testing *Precision* at the forecast level means that forecasts in years with more forecasts will have greater (undue) influence over the results than forecasts in years with fewer forecasts. *Precision* in these firm-year level analyses is calculated as the average precision for all forecasts made for the firm's fiscal year.

[10] We cannot use *FDI* in our firm-year level forecasts because a fiscal year may have multiple MEFs with different forecast dates.

We do not use *FDI_Fyend* for our previous forecast-level analyses because doing induces false positives in our measure - such a measure would capture projects announced after the MEF or AEF but before the end of the fiscal year. In untabulated results, the previous forecast-level analyses run with *FDI_Fyend* yield similar inferences but with weaker statistical significance because of the introduced errors.

The coefficients in Table 10 Column (1) (-0.013, t = -2.23) and Column (2) (-0.012, t = -2.22) are negative and significant, indicating that a larger number of FDI projects undertaken in a fiscal year is associated lower precision for the MEFs released for a said fiscal year.[11] The coefficients in Table 10 Column (3) (0.062, t = 1.86) and Column (4) (0.06, t = 1.82) are positive and significant, indicating that managers issue more earnings forecasts for fiscal years in which their firm undertakes more FDI projects and the coefficients in Table 10 Column (5) (0.055, t = 2.05) and Column (6) (0.054, t = 2.01) are positive and significant, indicating that managers issue more forecast revisions for fiscal years when their firms undertake more FDI projects. Untabulated logit regression results do not show evidence that the propensity for managers to issue MEFs is significantly higher with more FDI projects. Taken together, these results suggest that managers may be conscious of the forecasting difficulty presented by FDI projects and thus issue less precise earnings forecasts as well as a larger number of forecast revisions. The increase in forecast revisions also provides an alternative explanation for the increase in forecast horizon for MEFs as discussed previously (and tabulated in Table 9).

FDI and AEF Dispersion

To investigate the relationship that FDI has with analyst forecast dispersion, we utilize a modified version of *Model (2)* with the dependent variable being *Dispersion* and conduct the analysis at the firm-year level. *Dispersion* is the standard deviation of the analyst forecasts issued for a firm's fiscal year.

<Table 11>

[11] The results are similar and inferences are unchanged when we run this analysis at the management earnings forecast level with precision as the dependent variable FDI as the independent variable of interest.

The coefficients in Table 11 Column (1) (0.180, t = 2.69) and Column (2) (0.171, t = 2.58) are positive and significant, indicating that for firm-years with more FDI projects, there is greater analyst dispersion. Given that analysts experiencing uncertainty would issue earnings forecasts with greater dispersion (Barron et al., 1998), results in Table 11 further support the argument that FDI complicates firms' information environment.

Conclusion

We document that a larger number of FDI projects undertaken by a firm is associated with less accurate earnings forecasts (both management earnings forecasts and analyst earnings forecasts). These results are robust to alternative specifications of FDI based on the number of new projects or based on the spending amount of FDI projects. Our results show that this relationship is mitigated to some extent by a firm's managerial ability and also document that FDI projects are associated with shorter horizons (both MEFs and AEFs). Additionally, we document that FDI projects are associated with less precise MEFs with a higher revision frequency, suggesting that managers may be conscious of the forecasting difficulty associated with FDI projects. We also document that FDI projects are associated with higher dispersion in analyst earnings forecasts, providing further support that FDI projects induce uncertainty and make forecasting more difficult. Lastly, we also document that FDI projects are associated with less pessimistic MEFs and more pessimistic AEFs, highlighting the differences in which the responses of managers and analysts to information uncertainty may manifest.

Our study highlights the influence that FDI projects have on the information environment of the firm and our findings suggest that ample FDI disclosures may be useful to facilitate the decision-making of market participants.

A limitation of our study is that we do not distinguish between FDI projects for different functions (e.g., production vs R & D) and our measures do not distinguish between FDI made in different countries. Another limitation is that our study focuses on the annual earnings forecasts and is unable to shed light on whether these documented effects also pertain to quarterly earnings forecasts or non-earnings forecasts such as forecasts of revenue or cash flow.

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Appendix A – Variable definitions

Variables used in MEF regressions

Variable Name	Definition
MEF_Accuracy	Absolute difference between the manager's earnings forecast and the actual EPS multiplied by -100, scaled by beginning-of-the-period price. For range forecasts, upper bound of range is used.
MEF_Bias	Signed difference between the manager's earnings forecast and the actual EPS multiplied by 100, scaled by beginning-of-the-period price. For range forecasts, upper bound of range is used.
MEF_Horizon	Natural log of the number of days between the management earnings forecast data and the end of the fiscal year.
FDI	Natural log of one plus the number of FDI projects reported within 365 days prior to the management earnings forecast.
FDI_90	Natural log of one plus the number of FDI projects reported within 90 days prior to the management earnings forecast.
FDI_730	Natural log of one plus the number of FDI projects reported within 730 days prior to the management earnings forecast.
FDI_1095	Natural log of one plus the number of FDI projects reported within 1095 days prior to the management earnings forecast.
AFollow	Natural log of one plus the number of analysts issuing forecasts for the firm for this fiscal year.
AccQuality	Accruals quality as defined by Dechow and Dichev, 2002, multiplied by -1
BoardInd	Percentage of board that is comprised of independent directors based on data reported in Boardex.
Capex	Capital expenditures scaled by net PPE (Compustat CAPX or CAPXV scaled by PPENT).
EarnVol	Standard deviation of past 5 years earnings scaled by total assets (Stddev of Compustat NI / AT).
IndustryConc	Total sales of the top 5 firms in each industry (based on 2-digit SIC code) divided by total sales for the industry
InstOwn	Fraction of firm owned by institutional owners calculated using data reported on Thompson Reuters 13f database
LitRisk	Indicator variable that equals 1 if the firm belongs in the following industries with high litigation risk, SIC codes 2833–2836 (biotech), 3570–3577 and 7370–7374 (computers), 3670–3674 (electronics), 5200–5961 (retailing), 8731–8734 (R&D service) and suffers a 20 percent or greater decrease in earnings, and 0 otherwise
Complexity	Accounting Complexity Reporting score as defined by Hoitash and Hoitash 2018, 2022.
IntSegs	Natural log of one plus the number of international geographical segments reported by the firm.
Ability	Managerial Ability score as defined by Dermejian et al., 2012
MTB	Market to book at the beginning of the fiscal year calculated as market cap divided by book net assets (Compustat PRCC_F * CSHO / [(AT – LT) – (PSTKRV or PSTKL or PSTK) + TXDITC]).

Size	Market Cap at the beginning of the fiscal year (Compustat PRCC_F * CSHO)
PredictLoss	Indicator variable that equals 1 if the MEF predicts a loss, and 0 otherwise.

Variables used in AEF regressions

Variable Name	**Definition**
AEF_Accuracy	Absolute difference between the analyst's earnings forecast and the actual EPS multiplied by -100, scaled by beginning-of-the-period price.
AEF_Bias	Signed difference between the manager's earnings forecast and the actual EPS multiplied by 100, scaled by beginning-of-the-period price. For range forecasts, upper bound of range is used.
AEF_Horizon	Natural log of the number of days between the analyst earnings forecast data and the end of the fiscal year.
FDI	Natural log of one plus the number of FDI projects reported within 365 days prior to the analyst earnings forecast.
FDI_90	Natural log of one plus the number of FDI projects reported within 90 days prior to the analyst earnings forecast.
FDI_730	Natural log of one plus the number of FDI projects reported within 730 days prior to the analyst earnings forecast.
FDI_1095	Natural log of one plus the number of FDI projects reported within 1095 days prior to the analyst earnings forecast.
ForOp	Indicator variable that equals 1 if the firm reports at least 1 international segment and 0 otherwise.
IndustryConc	Total sales of the top 5 firms in each industry (based on 2-digit SIC code) divided by total sales for the industry.
Leverage	Firm leverage calculated as total long-term debt scaled by total assets (Compustat DLTT / AT).
AccQuality	Accruals quality as defined by Dechow and Dichev, 2002, multiplied by -1
AFollow	Natural log of one plus the number of analysts issuing forecasts for the firm for this fiscal year.
Complexity	Accounting Complexity Reporting score as defined by Hoitash and Hoitash 2018, 2022.
IntSegs	Natural log of one plus the number of international geographical segments reported by the firm.
Loss	Indicator that equals 1 if the firm reports a loss this fiscal year and 0 otherwise.
MTB	Market to book calculated as market cap divided by book net assets (Compustat PRCC_F * CSHO / [(AT – LT) – (PSTKRV or PSTKL or PSTK) + TXDITC]).
Size	Market Cap (Compustat PRCC_F * CSHO)
Capex	Capital expenditures scaled by net PPE (Compustat CAPX or CAPXV scaled by PPENT).
Big4	Indicator that equals 1 if the firm employs a "Big4" auditor for this fiscal year and 0 otherwise.
AuditorTenure	Indicator variable that equals 1 if the firm's auditor's number of years of service is greater or equal to 4 for this fiscal year.
AuditImportance	Importance of the firm as a audit client to their auditor, calculated as the audit fees divided by the total audit fees of their auditor for this fiscal year.

EarnVol	Standard deviation of past 5 years earnings scaled by total assets (Stddev of Compustat NI / AT).
EarnChange	Change in the net income of the firm calculated as absolute difference between previous year net income and current net income scaled by total assets.
AuditFees	Natural log of the dollar mount of audit fees for the current fiscal year.
Merger	Indicator that equals 1 if the firm announces a merger in this fiscal and 0 otherwise (1 if Compustat AQA or AQP is not missing and non-zero).

Table 1: MEF Sample

Panel A: Sample Selection

		Observations
1	Annual earnings (EPS) forecasts restricted to fiscal years 2013 - 2020	31,490
2	Remove pre-announcements	(411)
3	Remove announcements that cannot be matched to GVKEY	(6)
4	Remove announcements that do not have controls necessary for equation 1	(16,081)
5	Observations used for estimation	14,992

Panel B: Industry Composition

Two Digit SIC Industry Sector	Number of MEF	Percent of MEF
Agriculture (01–09)	57	0.38%
Mining (10–14)	59	0.39%
Construction (15–17)	232	1.55%
Manufacturing (20–39)	8925	59.53%
Telecommunication, Transportation, Utilities (40–49)	249	1.66%
Wholesale (50–51)	835	5.57%
Retailing (52–59)	1086	7.24%
Services (70–88)	3460	23.08%
Other	89	0.59%
Total	14992	100.00%

Panel C: MEF by Year

Fiscal Year	Number of MEF	Percent of MEF
2013	2257	15.05%
2014	2264	15.10%
2015	2142	14.29%
2016	2142	14.29%
2017	1840	12.27%
2018	1791	11.95%
2019	1655	11.04%
2020	901	6.01%
Total	14992	100.00%

Table 2: AEF Sample

Panel A: Sample Selection

		Observations
1	Annual earnings (EPS) forecasts restricted to fiscal years 2013 - 2020	4,104,353
2	Remove forecasts released after end of fiscal year	(104,724)
3	Retain only last forecast per analyst-firm-year	(3,508,551)
3	Remove announcements that cannot be matched to GVKEY	(38,252)
4	Remove announcements that do not have controls necessary for equation 2	(376,794)
5	Observations used for estimation	114,284

Panel B: Industry Composition

Two Digit SIC Industry Sector	Number of MEF	Percent of MEF
Agriculture (01–09)	46	0.04%
Mining (10–14)	10791	9.44%
Construction (15–17)	1342	1.17%
Manufacturing (20–39)	63840	55.86%
Telecommunication, Transportation, Utilities (40–49)	6478	5.67%
Wholesale (50–51)	4429	3.88%
Retailing (52–59)	5645	4.94%
Services (70–88)	21297	18.64%
Other	416	0.36%
Total	114284	100.00%

Panel C: AEF by Year

Fiscal Year	Number of AEF	Percent of AEF
2013	16456	14.40%
2014	15990	13.99%
2015	15397	13.47%
2016	14710	12.87%
2017	13734	12.02%
2018	13345	11.68%
2019	12851	11.24%
2020	11801	10.33%
Total	114284	100.00%

Table 3: Descriptive statistics

Panel A: Management Earnings Forecasts

Variable	N	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
MEF_Accuracy	14992	-0.7409	1.626406	-0.62814	-0.21759	-0.06963
MEF_Bias	14992	0.362947	1.609733	-0.15382	0.005665	0.327065
MEF_Horizon	14992	0.592786	0.38589	0.350685	0.641096	0.846575
FDI	14992	0.296977	0.57082	0	0	0.693147
FDI_90	14992	0.099893	0.303561	0	0	0
FDI_730	14992	0.455974	0.727016	0	0	0.693147
FDI_1095	14992	0.561689	0.817943	0	0	1.098612
FDI_New	14992	0.2089691	0.4707774	0	0	0
FDI_Spend	14992	0.971551	1.8400689	0	0	0.3509376
AccQuality	14992	-0.01774	0.011999	-0.02236	-0.01488	-0.00898
AFollow	14992	8.292449	4.297637	4.722222	7.875	11.1596
BoardInd	14992	0.77551	0.117566	0.666667	0.8	0.888889
Capex	14992	0.231965	0.12912	0.142504	0.197295	0.283602
EarnVol	14992	0.034255	0.03582	0.012913	0.022465	0.039508
IndustryConc	14992	0.442737	0.190282	0.311538	0.376072	0.538984
InstOwn	14992	0.710406	0.331636	0.681687	0.841322	0.928813
LitRisk	14992	0.091849	0.288822	0	0	0
Complexity	14992	5.951922	0.280447	5.777652	5.963579	6.156979
IntSegs	14992	0.867053	0.606926	0.693147	0.693147	1.098612
Ability	14992	-0.00645	0.141992	-0.09782	-0.0457	0.049799
MTB	14992	4.480996	7.458957	1.916483	3.01114	4.806629
Size	14992	8.386907	1.638991	7.252733	8.239446	9.43924
PredictLoss	14992	0.019744	0.139123	0	0	0

Panel B: Analyst Earnings Forecasts

Variable	N	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
AEF_Accuracy	114284	-2.8240247	11.73548	-0.9945972	-0.2635	-0.07288
AEF_Bias	114284	1.0921195	7.304685	-0.261896	-0.02864	0.266203
AEFHorizon	114284	4.7028567	1.1506189	4.0430513	4.2195077	5.6869754
FDI	114284	0.2726552	0.579808	0	0	0
FDI_90	114284	0.0976651	0.306553	0	0	0
FDI_730	114284	0.4156023	0.741317	0	0	0.693147
FDI_1095	114284	0.5128244	0.839425	0	0	0.693147
FDI_New	114284	0.1972436	0.4907642	0	0	0
FDI_Spend	114284	0.8682708	1.8053033	0	0	0
ForOp	114284	0.8093084	0.392848	1	1	1
AccQuality	114284	-0.0200327	0.015201	-0.0256984	-0.01577	-0.00946
IndustryConc	114284	0.4250279	0.17788	0.3108336	0.359663	0.514511
Leverage	114284	0.2597401	0.192499	0.1192865	0.243001	0.370119
AFollow	114284	2.9891774	0.609512	2.5649494	3.091043	3.433987
Complexity	114284	5.9306387	0.30239	5.7300998	5.937536	6.144186
IntSegs	114284	1.4444757	0.736719	1.0986123	1.609438	1.94591
Loss	114284	0.2365773	0.424982	0	0	0
MTB	114284	4.5420431	8.351153	1.5968873	2.829389	4.898054
Size	114284	8.5255009	1.85425	7.2968821	8.472417	9.76253
Capex	114284	0.2395661	0.148185	0.1359929	0.201243	0.303332
Big4	114284	0.8985685	0.301901	1	1	1
AuditorTenure	114284	0.9266651	0.260687	1	1	1
AuditImportance	114284	0.000227004	0.000753	0.000023818	4.91E-05	0.000131
EarnVol	114284	0.0519371	0.060024	0.0163997	0.031211	0.059608
EarnChange	114284	0.0477518	0.069222	0.009442	0.022686	0.055451
AuditFees	114284	14.9119931	1.067818	14.1562594	14.84905	15.64006
Merger	114284	0.4610269	0.498481	0	0	1

Table 4

Panel A: Management Earnings Forecast (MEF) Accuracy

	(1) Full Sample	(2) FDI-engaging Firms
FDI	**-0.162*** **	**-0.145*** **
	(-3.83)	**(-3.58)**
AccQuality	8.890***	9.019***
	(3.25)	(2.97)
AFollow	-0.019*	-0.012
	(-1.67)	(-0.88)
BoardInd	0.628*	0.392
	(1.84)	(1.06)
Capex	0.081	-0.292
	(0.21)	(-0.55)
EarnVol	-4.003***	-3.078
	(-2.90)	(-1.59)
Horizon	-0.870***	-0.824***
	(-8.68)	(-6.37)
IndustryConc	0.388	2.598
	(0.28)	(1.36)
InstOwn	0.346***	0.124
	(3.83)	(1.27)
LitRisk	-0.379***	-0.094
	(-3.04)	(-0.99)
AccComplexity	-0.875***	-0.749***
	(-6.08)	(-4.63)
IntSegs	-0.028	-0.032
	(-0.56)	(-0.55)
Ability	0.120	0.140
	(0.49)	(0.48)
MTB	0.008***	0.006**
	(2.87)	(2.47)
Size	0.355***	0.277***
	(9.15)	(5.91)
PredictLoss	-1.008**	-0.338
	(-2.37)	(-1.29)
Industry / Year Fixed Effects	Yes	Yes
Observations	14,992	9,510
Adjusted R-squared	0.236	0.240

Two-tailed robust standard errors clustered by firm; *** p<0.01, ** p<0.05, * p<0.1

Panel B: Analyst Earnings Forecast (AEF) Accuracy

	(1) Full Sample	(2) FDI-Engaging Firms
FDI	**-0.944*** **	**-0.331*** **
	(-14.70)	**(-5.93)**
ForOp	2.639***	1.927***
	(13.46)	(3.62)
Horizon	-1.568***	-0.858***
	(-33.34)	(-25.27)
IndustryConc	1.331	7.676***
	(0.80)	(4.76)
Leverage	-4.361***	-1.964***
	(-12.11)	(-5.94)
AFollow	-1.887***	-0.596***
	(-11.51)	(-3.93)
Complexity	1.027***	-0.077
	(4.87)	(-0.46)
IntSegs	-0.122	0.070
	(-1.61)	(0.92)
Loss	-23.610***	3.996
	(-5.29)	(0.81)
MTB	-1.335***	-0.794***
	(-9.67)	(-6.35)
Size	0.016***	-0.005
	(3.77)	(-1.57)
Capex	2.128***	1.397***
	(25.41)	(14.64)
Big4	1.788***	-1.058**
	(4.34)	(-2.55)
AuditorTenure	0.568*	0.618
	(1.84)	(1.34)
AuditImportance	0.897***	1.034***
	(4.00)	(3.74)
EarnVol	-391.884***	-320.575*
	(-2.96)	(-1.94)
EarnChange	-10.644***	-6.648***
	(-8.02)	(-4.66)
AuditFees	-28.536***	-15.090***
	(-21.72)	(-9.88)
Merger	-1.313***	-1.200***
	(-10.67)	(-12.53)
Industry / Year Fixed Effects	Yes	Yes
Observations	114,284	63,474
Adjusted R-squared	0.219	0.193

Two-tailed robust standard errors clustered by analyst; *** p<0.01, ** p<0.05, * p<0.1

Table 5: Interaction between FDI and Managerial Ability

Panel A: Management Earnings Forecast (MEF) Accuracy

	(1) Full Sample	(2) FDI-Engaging Firms
FDI	**-0.292***** **(-2.61)**	**-0.238**** **(-2.48)**
FDI * Top Ability	**0.273**** **(2.04)**	**0.249**** **(2.20)**
Top Ability	-3.056 (-1.28)	-7.985** (-2.20)
Controls	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes
Observations	5,985	3,746
Adjusted R-squared	0.301	0.348

Two-tailed robust standard errors clustered by firm; *** p<0.01, ** p<0.05, * p<0.1

Panel B: Analyst Earnings Forecast (AEF) Accuracy

	(1) Full Sample	(2) FDI-Engaging Firms
FDI	**-2.094***** **(-10.78)**	**-0.887***** **(-5.48)**
FDI * TopAbility	**1.498***** **(7.45)**	**0.832***** **(5.06)**
TopAbility	2.545 (0.63)	-4.226 (-1.15)
Controls	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes
Observations	45,586	24,239
Adjusted R-squared	0.268	0.346

Two-tailed robust standard errors clustered by analyst; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Alternative windows

Panel A: Management Earnings Forecast (MEF) Accuracy

	(1)	(2)	(3)	(4)
FDI_90	**-0.226***** **(-4.21)**			
FDI_365		**-0.162***** **(-3.83)**		
FDI_730			**-0.136***** **(-3.58)**	
FDI_1095				**-0.130***** **(-3.46)**
Controls	Yes	Yes	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	14,992	14,992	14,992	14,992
Adjusted R-squared	0.211	0.212	0.212	0.213

Two-tailed robust standard errors clustered by firm; *** p<0.01, ** p<0.05, * p<0.1

Panel B: Analyst Earnings Forecast (AEF) Accuracy

	(1)	(2)	(3)	(4)
FDI_90	**-1.439***** **(-13.57)**			
FDI_365		**-0.342***** **(-5.76)**		
FDI_730			**-0.230***** **(-12.06)**	
FDI_1095				**-0.094***** **(-5.05)**
Controls	Yes	Yes	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	114,284	63,474	114,284	63,474
Adjusted R-squared	0.218	0.193	0.218	0.193

Two-tailed robust standard errors clustered by analyst; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Alternative Specifications

Panel A: Management Earnings Forecast (MEF) Accuracy

	(1) Full Sample	(2) FDI-engaging Firms	(3) Full Sample	(4) FDI-engaging Firms
FDI_New	**-0.181***** **(-3.45)**	**-0.171***** **(-3.45)**		
FDI_Spending			**-0.045***** **(-3.79)**	**-0.034***** **(-3.08)**
Controls	Yes	Yes	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	14,992	9,510	14,992	9,510
Adjusted R-squared	0.236	0.240	0.236	0.239

Two-tailed robust standard errors clustered by firm; *** p<0.01, ** p<0.05, * p<0.1

Panel B: Analyst Earnings Forecast (AEF) Accuracy

	(1) Full Sample	(2) FDI-Engaging Firms	(3) Full Sample	(4) FDI-Engaging Firms
FDI_New	**-0.965***** **(-13.89)**	**-0.342***** **(-5.76)**		
FDI_Spending			**-0.254***** **(-13.49)**	**-0.094***** **(-5.30)**
Controls	Yes	Yes	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	114,284	63,474	114,284	63,474
Adjusted R-squared	0.218	0.193	0.218	0.193

Two-tailed robust standard errors clustered by analyst; *** p<0.01, ** p<0.05, * p<0.1

Table 8: Additional analysis – FDI and Earnings Forecast Bias

	MEF Bias		AEF Bias	
	(1) Full Sample	(2) FDI-Engaging Firms	(3) Full Sample	(4) FDI-Engaging Firms
FDI	**-0.162*** (-3.83)**	**-0.145*** (-3.58)**	**0.398*** (11.94)**	**0.202*** (6.97)**
Controls	Yes	Yes	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	14,992	9,510	114,284	63,474
Adjusted R-squared	0.236	0.240	0.135	0.111

Two-tailed robust standard errors clustered by firm for MEF, by analyst for AF; *** p<0.01, ** p<0.05, * p<0.1

Table 9: Additional analysis – FDI and Earnings Forecast Horizon

	MEF Horizon		AEF Horizon	
	(1) Full Sample	(2) FDI-Engaging Firms	(3) Full Sample	(4) FDI-Engaging Firms
FDI	**-0.044*** (-3.04)**	**-0.055*** (-3.39)**	**-0.094*** (-8.04)**	**-0.133*** (-10.40)**
Controls	Yes	Yes	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	14,992	9,510	114,284	63,474
Adjusted R-squared	0.032	0.041	0.014	0.010

Two-tailed robust standard errors clustered by firm for MEF, by analyst for AEF; *** p<0.01, ** p<0.05, * p<0.1

Table 10: Additional analysis – MEF Precision, Frequency, and Revisions

	Precision		Frequency		Revisions	
	(1) Full Sample	(2) FDI-Engaging Firms	(3) Full Sample	(4) FDI-Engaging Firms	(5) Full Sample	(6) FDI-Engaging Firms
FDI_Fyend	**-0.013** (-2.23)**	**-0.012** (-2.22)**	**0.062* (1.86)**	**0.060* (1.82)**	**0.055** (2.05)**	**0.054** (2.01)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,404	3,397	10,414	10,377	10,414	10,377
Adjusted R-squared	0.217	0.218	0.377	0.377	0.334	0.335

Two-tailed robust standard errors clustered by firm; *** p<0.01, ** p<0.05, * p<0.1

Table 11: Additional analysis – AEF Dispersion

	Dispersion	
	(1) Full Sample	(2) FDI-Engaging Firms
FDI_Fyend	**0.180*** (2.69)**	**0.171** (2.58)**
Controls	Yes	Yes
Industry / Year Fixed Effects	Yes	Yes
Observations	10,044	10,012
Adjusted R-squared	0.063	0.062

Two-tailed robust standard errors clustered by analyst; *** p<0.01, ** p<0.05, * p<0.1