Tracking Analysts along Technological Links

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Abstract: Using U.S. patent citations, we find that the number of analyst following and earnings forecast accuracy are positively related to a firm's technological links with other firms in the market. The likelihood of an analyst's coverage and forecast accuracy increase in the firm's technological links with other firms the analyst covers. Further analysis shows that the positive effects of technological links are more pronounced for firms with more uncertain business prospects, and are driven by both within- and across-industry technological links. Our results suggest that technological expertise allows analysts to exploit the informational complementarities across firms along the technological links.

Keywords: Technological links, analyst coverage, forecast accuracy, portfolio, commonality, expertise, industry specialization

1. Introduction

Given the prominent role that financial analysts play in capital markets, academic researchers and practitioners have strived to understand analysts' decision processes, such as the choice to include a particular firm in their coverage portfolio, and the various information sources they rely on for their research analysis. In this study, we investigate how a firm's technological links with other firms affect analysts' coverage decisions and earnings forecast accuracy. Two main intuitions underlie our study. First, commonality exists between two technologically related firms. Second, analysts benefit from complementary information shared through the technological links.

The literature provides valuable insights on the economic determinants of analyst coverage and forecast accuracy based on firm-specific characteristics (e.g., Bhushan, 1989; Lehavy et al., 2011) and analyst-specific attributes (e.g., Clement, 1999; Clarke and Subramanian, 2006). Recent studies have explored the impact of linkage among firms on analysts' research activities. Consistent with anecdotal evidence (e.g., Brown et al., 2015), O'Brien and Tan (2015) and Bradley et al. (2016) find industrial commonality to be a dominant factor in explaining analysts' coverage decisions and forecast performance. Recent research further suggests that the economic links in the product market, such as product similarity (Hsu et al., 2014) and supplier-customer relationships (Guan et al., 2014), also have positive effects on analysts' portfolio choices and forecast accuracy.

Technology innovation is a key factor in determining a firm's comparative competitiveness and long term productivity growth (Schumpeter, 1942). A large body of literature shows the impact of technology innovation on a firm's growth (e.g., Lentz and Mortensen, 2008; Kogan, Papanikolaou, Seru, and Stoffman, 2016) and stock performance (e.g., Pakes, 1985; Austin, 1993; Hall, Jaffe, and Trajtenberg, 2005; Nicholas, 2008). A casual reading of sell-side reports indicates that analysts pay close attention to the technology development of the target firms. For example, on April 4, 2014 Steven Milunovich, a well-repsected analyst at UBS, issued a 14-page report on Apple's patents in health and automotive. Indeed, understanding the technologies might be an importantant edge an analyst could obtain. Take

Steven Milunovich ‘s portfolio as an example; it includes firms such as Apple, Dell, and IBM, which compete mainly in different product markets (mobile phone for Apple, computer for Dell, and business services for IBM). Moreover, he also follows companies such as Ingram Micro and Tech Data, which are distributors of technology products. Apparently, product market linkages (e.g., product market competitor or supply chain relationships) among those firms are relatively weak, if exist at all. However, these firms’ businesses are all closely related to information technologies. The strong technoligcal links but weak product market links among the firms followed by Steven Milunovich suggest that technological knowledge might be a key type of expertise possessed by analysts.

An emerging literature examines the effects of technological links on corporate decisions and performance (e.g. Bena and Li, 2014; Li, 2014; Qiu and Wan, 2014; and Li, Qiu, and Wang, 2015). Little is known, however, on the effects of technological links on analysts’ coverage decisions and forecast performance. We construct measures of a firm’s technological links with other firms at two different levels. Our firm-level measure captures a given firm’s aggregate technological links with other firms in the capital markets, while our firm-analyst-level measure captures the firm’s technological links with other firms already covered by a particular analyst. Following Jaffe (1986), we calculate the technological links between a firm and its peer firms as a correlation measure between their patent outputs across different technological classes. The higher the correlation of patent outputs between the firm and its peer firms, the greater the overlap in technology. Intuitively, a greater overlap in technology indicates that the firm and its peer firms are more likely to face similar technological shocks.

Using a large sample of analyst earnings forecasts from 1990 to 2006, we first investigate how a firm’s aggregate technological links with other firms affects the number of analysts who cover the firm. We show that the level of analyst coverage is positively related to the firm’s aggregate technological links with other firms. An increase of one standard deviation in the aggregate number of technological links increases the level of analyst coverage by 40.32%. Next, we examine the effect of a firm’s technological links with other firms on analysts’ coverage decisions at the firm-analyst level. We show that the greater a firm’s technological links with other firms already covered by an analyst, the more likely the analyst will continue or initiate the coverage of the firm. Our results suggest that a firm's technological links with other firms in an analyst's coverage portfolio have a significant bearing on the analyst's decision to cover the firm.

After establishing the positive effect of technological links on analysts' coverage decisions, we further investigate the effect of technological links on analysts' earnings forecast performance. We first show that analysts' forecast accuracy on a firm increases with the firm's aggregate technological links with other firms in the market. In terms of economic significance, when the firm's aggregate technological links increase by one standard deviation, the average forecast accuracy by the analysts covering the firm increases by 13.7%. Further, we examine the effect of technological links on analyst forecast accuracy at the firm-analyst level. We find that a firm's technological links with other firms in an analyst's existing portfolio are positively related to the analyst's forecast accuracy on the firm. Thus, the positive effect of technological links on analyst forecast accuracy echoes the positive effect on analyst coverage decisions, suggesting that information commonality as captured by technological links benefits analysts' information production.

Firms that produce similar products are also likely to use similar technologies. Therefore, an alternative explanation for our findings is that the technological links between a firm and its peer firms merely capture their underlying product market links. In this case, the effects of technological links on analyst coverage and forecast performance would be a result of the product market links. To evaluate this alternative explanation, we construct two additional measures of technological links. The first measure captures the technological links between a firm and the peer firms that are in the same industry as the firm, while the second measure captures the technological links between a firm and the peer firms that are in different industries.[1] We construct these two measures at the firm and firm-analyst levels, respectively. We find that our results hold even for the technological links between a firm and the peer firms

[1] Our industry classification is based on the Global Industry Classification Standard (GICS) following Bhojraj et al. (2003).

in different industries, suggesting that our findings are unlikely to be driven by the product market links.

Moreover, we examine whether the positive effects of technological links on analyst coverage and forecast accuracy vary across firms associated with different levels of uncertainty in business prospects, as proxied by firm size, firm age, RE/TE, stock return volatility, and earnings loss. Because firm commonality with respect to technological links should benefit analysts more when information is more difficult to obtain, we expect the positive effects of technological links on analyst coverage and forecast accuracy to be more pronounced for firms associated with greater uncertainty in business prospects. We find evidence consistent with this expectation.

Finally, we investigate whether analysts' technological expertise is related to their industry specialization. We are interested to see whether there is a complementary or substitutive relationship between analysts' industry specialization and technological expertise. We find that analysts' technological expertise built on across-industry technological links could substitute analysts' industry specialization in coverage decisions. For analysts' earnings forecast accuracy, the effect of technological expertise is largely unaffected by analysts' industry specialization.

Our paper makes the following contributions to the literature. First, we examine the effects of technological links on analysts' coverage choices and forecast performance. Our research addresses the call of Beyer et al. (2010) for studies to fill the gap in our understanding of analysts' portfolio choices.[2] Our results suggest that analysts' existing coverage portfolios predict both the kind of firms to be covered and their forecast performance on these firms.

Second, we contribute to the analyst expertise literature (e.g., Clement et al., 2007; Kadan et al., 2012) by providing a new method to measure analysts' technological expertise, and showing that the effects of analysts' technological expertise on their coverage decisions and

[2] Specifically, Beyer et al. (2010, p. 329) call for more research on the effect that analysts' coverage portfolios have on their coverage decisions.

forecast performance are distinct from that of industry specialization.[3] Although studies show that covering multiple industries could result in lower forecast accuracy (Clement, 1999; Kini et al., 2009), we find that technological links contribute to forecast performance by allowing analysts to extract complementary information across industries.

Third, our findings echo the importance of technological links documented in previous studies by showing that firm commonality with respect to technological links facilitates analysts' coverage decisions and contributes to their forecast performance. We extend the information transfer literature beyond the commonly studied product market (e.g., Pandit et al., 2011). We investigate a less studied, yet important economic link, namely technological links, and show that the informational commonality along technological links benefits the information production of financial analysts.

The rest of the paper proceeds as follows. In Section 2, we review the literature and develop our hypotheses. Section 3 describes the sample and key variables. In Sections 4 and 5, we examine whether technological links affect analysts' coverage decisions and improve analyst forecast accuracy, respectively. In Section 6, we examine how the effects of technological links on analyst coverage and forecast accuracy vary across firms associated with different levels of information uncertainty. In Section 7, we investigate whether analysts' industry specialization and technological expertise substitute or complement each other. Section 8 concludes.

2. Literature Review and Hypothesis Development

In this section, we first review the relevant literature on analysts' expertise and corporate innovation. We then develop our hypotheses regarding the effects of technological links on analysts' coverage decisions and forecast accuracy.

2.1 Literature Review on Analysts' Expertise

Sell-side equity analysts acquire information from various resources and disseminate their research outputs to investors. Due to the constraints on resources and demand for their research services, analysts and their brokerage firms need to decide on which firms to cover.

[3] Lambert, Matolcsy, and Wyatt (2015) find that analysts' industry knowledge includes the implications of technological conditions within industries for firms' future earnings.

However, analysts' coverage portfolios are not comprised of isolated entities. The literature indicates that analysts tend to focus on a small number of industries (e.g., Gilson et al., 2001; Piotroski and Roulstone, 2004; Chan and Hameed, 2006). Industry specialization allows analysts to achieve economies of scale in acquiring value relevant information, which improves their forecast performance. Gilson et al. (2001) document that firms emerging from conglomerate breakups attract more coverage from analysts specializing in the subsidiary firms' industries, and that the improvement in forecast accuracy is greater for industry specialists than for non-specialists. O'Brien and Tan (2015) find that while geographic proximity affects analysts' information acquisition, analysts' industry specialization is the most important factor in their decision to cover IPO firms. In a survey of sell-side analysts, Brown et al. (2015) show that industry knowledge and the similarity of a given firm with other firms in an analyst's existing portfolio are the two most important factors in analysts' decisions to cover the firm.

Analysts do not necessarily specialize by industries. Kini et al. (2009) find that analysts' geographic or industry specialization depends on the extent to which firms *within* a country or sector and firms *across* country-sectors are exposed to common economic forces. Kadan et al. (2012) find that recommendation portfolios based on analysts' ranking of industries relative to each other generate abnormal returns, suggesting that analysts exhibit across-industry expertise. They also find that the two dimensions of analysts' industry expertise (across-industry and within-industry) complement each other.

Despite the importance of analysts' specialization, few studies have explored the channels through which analysts accumulate such expertise. Using hand-collected biographical information, Bradley et al. (2016) show that analysts are more accurate in their forecasts when they have previous industry experience related to the forecasted firms. In this case, their forecast accuracy is enhanced by their deep understanding of the industry fundamentals and better knowledge of each firm's position within the industry. These findings suggest that analysts benefit from within-industry commonality. Such commonality may also exist among firms producing similar products but across conventionally defined industries. Hsu et al. (2014) find that analysts are more likely to add (drop) a firm if its products are more (less) similar to other firms' in their portfolios and that analysts' forecast accuracy increases with the product similarity in their coverage portfolios. In a similar vein, Guan et al. (2014) show that analysts cover both suppliers and customers to explore the informational complementarity along the supply chain. Our paper suggests that analysts could develop and strengthen their forecast expertise by examining the technological links across firms, which may span different industries.

2.2 Corporate Innovation and Technology

Prior literature finds that firm innovation and technology affect future cash flows, expected profit and market performance. For example, Matolcsy and Wyatt (2008) show that a firm's underlying technology innovation conditions as captured by the success rate of past technological investments, technology complexity, and the technology development period drives its future earnings growth and the market value of equity.[4]

Despite the importance of technology to firm performance and valuation, only a limited number of studies examine the impact of analysts' technology knowledge on their forecast activities. Palmon and Yezegel (2013) find that the value of analysts' recommendations is significantly greater for firms that are more intensely engaged in R&D investments, suggesting that financial analysts contribute more to the price discovery process of R&D-intensive firms. Merkley (2014) finds that narrative R&D disclosure quantity is positively related to analyst following and forecast accuracy and negatively related to analyst forecast dispersion. Lambert, Matolcsy, and Wyatt (2015) find that analysts' industry knowledge includes an understanding of the technological conditions to which the firms' investments are exposed and how these technological conditions within industries map into future earnings. We add to this literature by showing that a firm's technology proximity to peer firms is positively related to analyst following and forecase accuracy.

2.3 Hypothesis Development

A variety of economic links may exist between a pair of firms. For instance, one could be the other's competitor, supplier, customer, or strategic partner. One important type of economic

[4]See Grandi, Hall, and Oriani (2009) for a literature review.

link arises when two firms adopt similar technologies; that is, the two firms are technologically related.

Commonality is likely to exist between two technologically related firms. For instance, a technological shock to one firm could also affect the other firm. The commonality between technologically related firms becomes more complicated when two related firms compete in developing new technology. A successful R&D project in one firm may have both negative and positive effects on its competitor. On the one hand, the new technology gained by one firm may put its competitor in a more disadvantaged position. On the other hand, with the spread of knowledge, the new knowledge produced by the firm may benefit its competitor's R&D projects in related technologies (Bloom et al., 2013). Regardless of which effect is dominant, the supply side of information about one firm's technological development could reveal to analysts the other firm's prospects.

Given that a firm's competitiveness and hence its value increasingly rely on technological innovation, investors need to understand the prospects of the firm's technology and the external environment that may affect its technological innovation. When the firm's technology is similar to many peer firms', the firm is likely to face more threats (e.g., aging technology due to peer firms' innovation) and/or more opportunities (e.g., merger with a peer firm). Thus, the greater the overlap between the firm's technology and its peer firms', the more variation in the firm's business prospect, which is likely to result in higher demand for analyst forecasts on its future performance. In response to such demand, analysts may have incentives to take into account the firm's technological links in their coverage decisions. The above arguments based on both supply and demand sides lead to our Hypothesis 1a.

H1a: The number of analysts that follow a firm increases with the extent to which the firm is technologically related to other firms in the market.

Research indicates that specializing in a small number of industries could reduce analysts' cost of information production. In a similar vein, analysts could reduce the cost of information production by choosing a coverage portfolio that includes firms built on similar technologies. Given that technological innovation is inherently uncertain, producing information about the prospects of an innovative firm could be a difficult and costly task, which highlights the importance for analysts to specialize in certain types of technologies to explore the commonality along technological links. This reasoning leads to our Hypothesis 1b.

H1b: The likelihood of an analyst covering a firm increases with the firm's technological links to other firms in the analyst's coverage portfolio.

While a firm's technological links to its peer firms may increase uncertainty in its business prospects and hence reduce analysts' forecast accuracy, analysts could benefit from incorporating complementary information gained from other firms into their forecasts for that firm. We expect the benefit from the information complementarity gained from the technological proximite firms to dominate the adverse impact due to the increase of uncertainty in business prospect. Our Hypothesis 2a is stated as follows.

H2a: An analyst's earnings forecast accuracy increases with the extent to which the forecasted firm is technologically related to other firms in the stock market.

Technological links among a group of firms may allow an analyst to gain technology expertise by specializing in certain technologies and employing complementary information obtained from overlapping technologies. Such technology expertise should reduce the analyst's information uncertainty and increase forecast accurarcy. Our Hypothesis 2b is thus stated as follows.

H2b: An analyst's earnings forecast accuracy increases with the forecasted firm's technological links to other firms in the analyst's coverage portfolio.

3. Sample Formation and Variable Construction

3.1. Sample Selection

We obtain data on firms' patenting activity from the National Bureau of Economics Research (NBER) patent citations data file. The patent data file provides information such as the number of citations made and the cited patent IDs, number of citations received and the citing patent IDs, patent application, and award year (see Hall, Jaffe, and Trajtenberg (2001) for details). To meaningfully measure the technological links across the firms, we focus on firms that are granted at least one patent during 1990 to 2006, which is the latest sample period available to us from the NBER patent database. We obtain other data from various sources, including I/B/E/S for analyst-related variables, Compustat for accounting information, the Center for Research in Security Prices (CRSP) for stock returns and other market-related variables, First Call for management forecasts, and Thomson Reuters S34 file for institutional holdings.

We construct two samples: one at the firm level and the other at the firm-analyst level. Table 1 reports the details of the results of our sampling procedures. The patent information from the NBER database allows us to estimate the levels of technological links (described below) from 1990 to 2006. Due to the well-known patent approval lag between application and award, the data coverage of patents in 2006 was poor. Hence, our firm level sample ends in 2005. We start from 117,926 Compustat/CRSP matched firm-year observations (15,883 firms). We require firms to have common shares traded on NYSE/AMEX/NASDAQ and to have Standard & Poor's Global Industry Classification Standard (GICS), which leaves 93,904 observations (12,876 firms). Retaining firms with at least one patent during our sample period reduces the sample to 37,506 observations (4,168 firms).[5] Because our dependent variables are measured at year $t+1$, we also remove observations where year t is a firm's final year in Compustat to ensure meaningful interpretations. After excluding missing values for the required variables, we have 33,937 observations (3,921 firms) and 25,965 observations (3,426 firms), respectively, for the firm level coverage (H1a) and accuracy (H2a) analysis.

We need one extra year to measure analysts' forecast activities. Therefore, our firm-analyst level sample ends in 2006. We follow the same screening procedure as the above to construct our firm-analyst level samples. For our firm-analyst level coverage test (H1b), we have 216,029 observations (3,434 firms and 7,628 analysts); for our firm-analyst level accuracy test (H2b), we have 216,201 observations (3,388 firms and 7,564 analysts).

3.2. Empirical Proxies for Technological Links

Using information on patents across different technology classes, we construct *Aggregate Technological Proximity* to measure a firm's technological links with other firms. Similar to the

[5] Although this step excludes about 60% of the firm-year observations, we lose less than 30% of the total market cap.

bilateral technological proximity measure in Jaffe (1986), we compute a firm's *Aggregate Technological Proximity* with other firms as $\frac{S_{i,t}S'_{-i,t}}{\sqrt{S_{i,t}S'_{i,t}}\sqrt{S_{-i,t}S'_{-i,t}}}$, where the vector $S_{i,t} = (s_{i,1,t}, \ldots, s_{i,k,t}, \ldots, s_{i,K,t})$ captures the scope of technologies of firm *i*, and $S_{-i,t} = (s_{-i,1,t}, \ldots, s_{-i,k,t}, \ldots, s_{-i,K,t})$ captures the scope of technologies of firms other than firm *i*. The subscript *k* is the technology class index, and *K* (which is equal to 421) is the total number of U.S. patent classes. The scalar $s_{i,k,t}$ ($s_{-i,k,t}$) is the ratio of the number of patents awarded to firm *i* (firms other than *i*) in technology class *k* to the total number of patents awarded to firm *i* (firms other than *i*) within the past three years of the application year. This correlation measure ranges from zero to one, with larger values indicating greater technological proximity between firm *i* and other firms.[6]

We construct *Aggregate Technological Proximity* at two different levels. In our firm level analyses, we compute the correlation measures between firm *i* and all other firms in our sample. This firm-level measure captures firm *i*'s technological similarity to other firms in the stock market. In our firm-analyst level analyses, we compute the correlation measure between firm *i* and other firms covered by a particular analyst. This firm-analyst level measure captures firm *i*'s technological similarity to other firms covered by the analyst.

Because firms in the same industry are more likely to use similar technologies, one concern is that our measures of technological links may overlap with the product market similarity. Consequently, our results may be driven by product market links rather than technological links. To address this concern, for both the firm level and firm-analyst level analyses, we further construct within-industry and across-industry measures of *Aggregate Technological Proximity*, respectively. In particular, the firm level (the firm-analyst level) *Within-Industry Aggregate Technological Proximity* is the technological links between firm *i* and all other firms in the stock market (in the analyst's coverage portfolios) that are in the same industry as firm *i*. The firm level (the firm-analyst level) *Across-Industry Aggregate*

[6] In our setting, firms are only technologically linked if they produce patentable R&D in similar fields. To the extent that technologies that link firms are in areas where they do not necessarily produce R&D, our measure produces a low boundary of the technology links between firms, which biases against our results. We use technological links and technological proximity interchangeably.

Technological Proximity is the technological links between firm *i* and all other firms in the stock market (in the analyst's coverage portfolios) that are in industries different from firm *i*. Following Bhojraj et al. (2003), we use the GICS to classify industries.

3.3. The Scale and Scope of Firms' Technologies

To control for firm characteristics related to technologies, we construct the following two variables to measure the scale and scope of firms' technologies in our analysis.

Patent Count: the number of patents a firm is awarded within the past three years of the application year. This variable captures the scale of the firm's technological development.

Technological Concentration: following Hirshleifer et al. (2014), we construct *Technological Concentration* as follows,

$$Technological\ Concentration_{i,\,t} = \sum_{k=1}^{K}\left(\frac{n_{i,k,t}}{\sum_{k=1}^{K} n_{i,k,t}}\right)^2 \qquad (1)$$

where $n_{i,k,t}$ is the number of patents awarded to firm *i* in technology class *k* within the past three years of the application year, and K is the total number of patent classes. *Technological Concentration* ranges between 0 and 1 and captures the scope of the firm's technologies. At the analyst level, we construct a *Technological Concentration* variable in a similar way. We set *Technological Concentration* to zero if a firm has no patent applications in the past three years.

3.4. Control Variables

In our regressions, we include control variables that are shown to affect analyst coverage and forecast accuracy in the literature. At the firm level, we follow Bhushan (1989), Lang and Lundhum (1996), and McNichols and O'Brien (1997) and control for market capitalization ($Size$), market-to-book ratio (MB), profitability (ROA), earnings loss (*Loss*), stock returns (*Ret*), return volatility ($RetVolaty$), institutional ownership ($InstHold$), the number of management forecasts ($MgmtFcst$), and the number of business segments ($Segm$). At the firm-analyst level, we also control for analyst characteristics. In particular, for the analyst coverage analysis, we control for the number of firms covered by the analyst ($NCom$) and the analyst's firm-specific experience ($FirmExp$), following prior studies such as Liang et al. (2008) and O'Brien and Tan (2015). For the forecast accuracy analysis, we control for the forecast horizon (Age), the general forecast experience of an analyst ($GenExp$), the number of industries the analyst covers ($NInd$), and whether the analyst works for a big broker ($TopB$).

Research shows that analysts' industry expertise is an important determinant of their decision to cover a particular firm. Therefore, for each firm-analyst pair, we control for the analyst's expertise in the firm's industry. Specifically, we calculate $pInd_{k,i,t}$, which is the number of same GICS-industry firms (other than firm i) covered by analyst k divided by the total number of firms covered by analyst k in year t.[7]

3.5. Summary Statistics

Panel A of Table 2 reports the summary statistics of the firm level sample. On average, our sample firms are covered by seven analysts, with a price-scaled earnings forecast error of 0.016. The average *Aggregate Technological Proximity* is 0.089. The average *Within-Industry Aggregate Technological Proximity* (0.197) is higher than the average *Across-Industry Aggregate Technological Proximity* (0.072), consistent with the expectation that firms in the same industry are more likely to use similar technologies. However, the average *Across-Industry Aggregate Technological Proximity* (0.072) is fairly close to the average *Aggregate Technological Proximity* (0.089), which suggests that a significant proportion of the technological links are across-industry. *Patent Count* is highly skewed, with a median of 2 and a mean of 29.355. We thus use a log transformation of this variable in our regression analyses. The average firm's *Technological Concentration* is 0.357, suggesting that firms generally concentrate on a small number of technology classes.

Panel B of Table 2 reports the summary statistics of the firm-analyst level sample. On average, our sample analysts have 5.6 years of forecast experience, and have covered firms for at least 2 years. These analysts, on average, cover 16 firms and 4 industries. Analyst industry expertise ($pInd_{k,i,t}$) has a mean of 0.441, suggesting that about 44% of other firms (other than firm i) covered by analyst k as of year t belong to the same industry as firm i. Nearly 53% of the

[7] The results (untabulated) are qualitatively similar if we use an indicator variable $dInd_{k,i,t}$ to measure analysts' industry expertise. $dInd_{k,i,t}$ takes the value of 1 if there is at least one other firm technically connected with firm i in analyst k's portfolio at year t, and 0 otherwise.

forecasts are provided by analysts working with brokers in the top size decile. The average firm's *Aggregate Technological Proximity* (*Within-Industry and Across-Industry Aggregate Technological Proximity*) at the analyst level is 0.247 (0.233 and 0.116), which is significantly higher than the corresponding value at the firm level, suggesting that analysts tend to specialize in certain technologies.

To provide preliminary evidence on the usefulness of technological expertise on analysts' forecast performance incremental to their industry expertise, Table 3 shows summary statistics of analysts' proportional mean adjusted forecast errors (*PMAFE*) by two-way sorts of technological links and industry expertise based on the median cutoff values of the final firm-analyst level sample.[8] We define *PMAFE* as the ratio of the difference between the absolute forecast error (*AFEijt*) by analyst *i* for firm *j* at time *t* and the mean absolute forecast error (*avgAFEjT*) of all of the forecasts for firm *j* for fiscal year *T*, to the mean absolute forecast error *avgAFEjT*, i.e., $PMAFE_{ijt} = (AFEijt\text{-}avgAFEjT)/avgAFEjT$. We find that controlling for industry expertise (*pInd*), analysts are more accurate in covering firms that are more technologically linked to their existing coverage portfolio. For example, for the subsample of analysts with high industry expertise, the difference in *PMAFE* between the high- and low-technological proximity groups is 0.041, which is statistically significant. Similarly, controlling for technological links, analysts' industry expertise improves their forecast accuracy. All of the differences are statistically significant at the conventional levels ($p<0.05$).

4. Technological Links and Analyst Coverage

In this section, we conduct both firm level and firm-analyst level analyses to examine whether a firm's technological links with other firms affect its coverage by financial analysts.

4.1. Firm Level Evidence

Following Rock et al. (2001) and Bae et al. (2008), we use the negative binomial model to test Hypothesis H1a, which relates analyst coverage to a firm's technological links with other

[8] We assess analysts' relative forecast accuracy because we intend to remove confounding factors, such as firm characteristics, at the univariate level.

firms in the stock market. Our results are qualitatively similar if we use OLS regressions instead. Our regression model takes the following generic form,

$$NANA_{i,t+1} = \alpha + \beta_1 * Aggregate\ Technoloigal\ Proximity_{i,t} + \beta_2 * Patent\ Count_{i,t} + \beta_3 * Technological\ Concentration_{i,t} + \sum \gamma * FirmControls_{i,t} + \varepsilon_{i,t}, \qquad (2)$$

where $NANA_{i,t+1}$ is the total number of analysts covering firm *i* in year *t+1*; and $Aggregate\ Technological\ Proximity_{i,t}$ is the firm-level measure of technological links that captures the aggregate technological proximity of firm *i* with other firms in the stock market. We report the *t*-values based on standard errors that are heteroskedasticity-consistent and clustered at the firm level.

We present the negative binominal regression results in Table 4. Columns (1) – (3) use the full sample. Column (1) is the baseline model without the firm level technological link measures. The results indicate that the number of analysts covering a firm is positively correlated with the firm's market capitalization, market-to-book ratio, return on assets, stock returns, volatility, institutional ownership, and the number of management forecasts, but negatively correlated with the number of segments.

In column (2), we augment the baseline model by including technological measures, such as *Patent Count*, *Technological Concentration*, and firm level *Aggregate Technological Proximity*. We find that the coefficient estimate on *Technological Concentration* is significantly positive, suggesting that analysts are more likely to cover firms with a relatively simple technology structure. More importantly, the coefficient estimate on *Aggregate Technological Proximity* is significantly positive. This result suggests that analyst coverage increases with a firm's technological links to other firms in the stock market, which is consistent with Hypothesis H1a. In terms of economic significance, the incident rate ratio (IRR) of *Aggregate Technological Proximity* is 3.734. Thus, an increase of one standard deviation in *Aggregate Technological Proximity* increases the level of analyst coverage by 40.32% (=0.108*3.734), which is economically significant.

In column (3), we replace *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. The coefficient on *Within-Industry Aggregate Technological Proximity* is 0.480, while the coefficient on *Across-Industry Aggregate Technological Proximity* is 0.750; both are significant at the one percent level. The difference between these two coefficients is significant at the five percent level, with a Chi-square value of 3.86. The IRR for *Within-Industry Aggregate Technological Proximity* is 1.617, while the IRR for *Across-Industry Aggregate Technological Proximity* is 2.118. Thus, it is unlikely that our results are driven purely by product market links, which relate more closely with *Within-Industry Aggregate Technological Proximity*. In columns (4) – (6), we replicate the analysis in columns (1) – (3) using the sample of firms that are covered by at least one analyst. The results are qualitatively similar.

4.2. Firm-Analyst Level Evidence

Hypothesis H1b is at the firm-analyst level and relates the likelihood that an analyst covers a firm to the firm's technological links with other firms in the analyst's portfolio. We first construct the firm-analyst coverage sample conditional on that an analyst covers a firm in year *t*. We then track whether this analyst chooses to continue or drop the coverage of the firm in year *t+1*. To test this hypothesis, we run the following logit regression:

$$\begin{aligned} COVER_{k,i,t+1} = \alpha &+ \beta_1 * Aggregate\ Technoloigal\ Proximity_{k,i,t} + \beta_2 * Patent\ Count_{i,t} \\ &+ \beta_3 * Technological\ Concentration_{i,t} + \sum \gamma * FirmControls_{i,t} + \\ &\sum \delta * AnalystControls_{k,i,t} + \varepsilon_{k,i,t}, \end{aligned} \quad (3)$$

where $COVER_{i,t+1}$ equals one if analyst k continues to cover firm *i* in year *t+1* and zero otherwise; and $Aggregate\ Technoloigal\ Proximity_{k,i,t}$ is the firm-analyst level measure of technological links that captures the aggregate technological proximity with other firms the analyst has covered in year *t*.

Columns (1) – (3) of Table 5 report the logit regression results. Column (1) is the baseline model that also controls for an analyst's expertise in a firm's industry (*pInd*). Consistent with our expectations, the coefficient estimate on *pInd* is significantly positive, suggesting that an analyst is more likely to cover a firm if the analyst has more expertise in the firm's industry.

Column (2) augments the baseline model by including technological measures such as *Patent Count*, *Technological Concentration*, and firm-analyst level *Aggregate Technological Proximity*. Consistent with Hypothesis H1b, the coefficient estimate on firm-analyst level *Aggregate Technological Proximity* is positive and significant at the 1% level.

Column (3) replaces *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. The coefficient estimates on both *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity* are positive and significant at the 1% level. The coefficient on *Across-Industry Aggregate Technological Proximity* is significantly larger than that on *Within-Industry Aggregate Technological Proximity*, with an unreported Chi-square value of 17.22. This suggests that across-industry technological links are more important for analysts' coverage decisions.

To shed more light on analysts' coverage decision processes, we conduct another test to investigate their choices on coverage initiations. We start with firms that are not covered by analyst k in year t but start being covered in year $t+1$. For each such firm, we identify up to five matching firms from the same industry that have at least one patent during our sample period and are not covered by analyst k in both year t and year $t+1$. We further require that the matching firms' book value of total assets be within 50% and 150% of that of the sample firms.[9] $Add_{k,i,t+1}$ is set to zero for the matching firms, and one otherwise. Columns (4) – (6) of Table 5 report the conditional logit regression results for this sample. Overall, return on assets loses significance, return volatility and the number of management forecasts become significantly positive, while the number of segments changes to significantly negative for this coverage initiation sample.

Column (4) is the baseline model controlling for firm characteristics and sample-firm-analyst fixed effects. Because analyst characteristics are invariant within each firm-analyst pair,

[9] We drop the focal firms if there are no matching firms.

analyst characteristics are not included as independent variables. The results indicate that analysts are more likely to initiate coverage of larger firms with higher growth opportunities, strong past stock performance, more volatile stock returns, more institutional holdings, and more management guidance, but less likely to initiate coverage of firms with earnings losses and more business segments.

Column (5) augments the baseline model by including technological measures, such as *Patent Count* and firm-analyst level *Aggregate Technological Proximity*.[10] Consistent with Hypothesis H1b, the coefficient estimate on firm-analyst level *Aggregate Technological Proximity* is significantly positive at the 1% level.

Column (6) replaces *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. The coefficient estimates on both *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity* are significantly positive at the 1% level. The difference between these two coefficients is not significant. Overall, both the firm level and firm-analyst level analyses indicate that analyst coverage is positively related to a firm's technological links with other firms, even after we control for analysts' industry expertise.

5. Technological Links and Forecast Accuracy

In this section, we examine whether a firm's technological links with other firms affect analysts' forecast accuracy on the firm.

5.1. Firm Level Evidence

To test Hypothesis H2a, which relates the consensus forecast accuracy of a firm to its technological links with other firms in the stock market, we run the following OLS regression:

$$AFE_{i,t+1} = \alpha + \beta_1 * Aggregate\ Technoloigal\ Proximity_{i,t} + \beta_2 * Patent\ Count_{i,t} + \beta_3 * Technological\ Concentration_{i,t} + \sum \gamma * FirmControls_{i,t} + \varepsilon_{i,t}, \quad (4)$$

[10] We do not control for technological concentration because this variable is analyst-year specific and thus invariant in the analyst-firm level tests.

where $AFE_{i,t+1}$ is the analyst forecast error for firm i in year $t+1$, measured as the absolute value of the difference between analysts' final consensus before the end of year $t+1$ and the actual earnings, scaled by the stock price at the beginning of the year. A smaller value of AFE indicates a more accurate earnings forecast. $Aggregate\ Technoloigal\ Proximity_{i,t}$ is the firm-level measure of technological links that captures a firm's aggregate technological proximity to other innovative firms in the stock market.

Table 6 reports the regression results. Column (1) is the baseline model. The results show that analyst forecast error is negatively related to firm market capitalization, market-to-book ratio, return on assets, stock returns, and institutional ownership, but positively related to past loss, stock return volatility, and the number of segments.

Column (2) augments the baseline model by controlling for technological measures such as *Patent Count*, *Technological Concentration*, and firm level *Aggregate Technological Proximity*. Consistent with Hypothesis H2a, we find that the coefficient on *Aggregate Technological Proximity* is significantly negative, suggesting that firms that share closer technological links to other firms in the stock market are associated with more accurate analyst forecasts.

Column (3) replaces *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. The coefficient estimates on both *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity* are significantly negative at the 1% level. Further, the coefficient on *Across-Industry Aggregate Technological Proximity* is significantly larger than that on *Within-Industry Aggregate Technological Proximity*, with a Chi-square of 8.68 and a *p*-value of 0.01 (untabulated).

The improvement in forecast accuracy is economically significant. When the *Aggregate Technological Proximity* increases by one standard deviation, the forecast error decreases by 0.0022 (= 0.108*2.033/100).[11] The sample average of the forecast error is 0.016, which

[11] We divide by 100 because we multiply the raw *Accuracy* measure by 100 in our regression analyses.

represents a 13.7% improvement on the sample mean. Consistent with Hypothesis H2a, our results in Table 6 suggest that a firm's technological links with other firms in the stock market help analysts improve their forecast accuracy.

5.2. Firm-Analyst Level Evidence on Forecast Accuracy

Our firm-analyst level Hypothesis H2b relates a firm's technological links with other firms in an analyst's portfolio to the analyst's forecast accuracy on the firm. To test this hypothesis, we run the following OLS regression:

$$\begin{aligned} AFE_{k,i,t+1} = {} & \alpha + \beta_1 * Aggregate\ Technoloigal\ Proximity_{k,i,t} + \beta_2 * Patent\ Count_{i,t} \\ & + \beta_3 * Technological\ Concentration_{k,t} + \sum \gamma * FirmControls_{i,t} \\ & + \sum \delta * AnalystControls_{k,i,t} + \varepsilon_{k,i,t} \end{aligned} \quad (5)$$

where $AFE_{k,i,t+1}$ is analyst *k*'s forecast error for firm *i* in year *t+1*, measured as the absolute value of the difference between analysts' final forecast before the end of year *t+1* and the actual earnings, scaled by the beginning year stock price.$Aggregate\ Technoloigal\ Proximity_{k,i,t}$ is the firm-analyst level measure of technological links that captures the aggregate technological proximity with other firms the analyst has covered in year *t*.[12]

Table 7 reports the regression results. Column (1) is the baseline model. The results show that forecast error is positively related to earnings loss (*Loss*), return volatility (*RetVolaty*), number of segments of the firm (*Segm*), forecast horizon (*Age*), and analyst firm experience (*FirmExp*), but negatively related to firm size (*size*), market to book ratio (*MB*), past performance (*ROA* and *Ret*), institutional holding (*InstHold*), the number of management forecasts (*MgmtFcst*), and the size of brokerage house (*TopB*).

Column (2) augments the baseline model by including technological measures, such as *Patent Count*, *Technological Concentration*, and firm-analyst level *Aggregate Technological Proximity*. Consistent with Hypothesis H2b, the coefficient estimate on firm-analyst level *Aggregate Technological Proximity* is significantly positive at the 1% level.

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[12] Prior studies use mean-adjusted analyst forecast errors by firm-year following Clement (1999) or alternatively, the rank of an analyst's forecast error following Hong and Kubiak (2003) to control for firm-year fixed effects.

Column (3) replaces *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. The coefficient on *Within-Industry Aggregate Technological Proximity* is negative but insignificant, while the coefficient on *Across-Industry Aggregate Technological Proximity* is negative and significant at the 1% level. This result indicates that technological links allow analysts to extract complementary information from firms in different industries.

With respect to economic significance, an increase of one standard deviation in *Aggregate Technological Proximity* leads to a decrease in forecast error by 0.00032 (= 0.247*0.129/100). Since the sample average of forecast error is 0.008, the change represents a 4% improvement on the sample average. A possible reason for the modest improvement in the earnings forecast is that once analysts decide to cover a firm, they have to spend extra effort in researching those firms that are beyond their previous knowledge base, which would mitigate the effect of technological links on their forecast accuracy.

Clement (1999) argues that controlling for firm-year effects could more effectively identify systematic differences in analysts' forecast accuracy. Therefore, in columns (4) – (6), we use $PMAFE_{k,i,t+1}$, the proportional mean absolute forecast error of analyst k for firm i in year $t+1$, as an alternative dependent variable. Similar to *AFE*, a lower value of *PMAFE* indicates greater forecast accuracy. Following Clement (1999), we also mean adjust all of the independent variables. Because all firm characteristics are invariant for a given firm-year, we exclude them from the regressions. The results of the technology related variables are qualitatively similar. With this specification, analysts' firm specific experience is significantly negative, consistent with Clement (1999). Analysts' industry expertise (*pIND*) is also significantly negative.

6. Information Uncertainty and the Effects of Technological Links

In the previous sections, we find that technological links are positively correlated with analysts' coverage likelihood and forecast accuracy. If the commonality along the technological links among firms indeed affects analysts' coverage decisions and their forecast accuracy, the effect should be stronger for firms with more uncertain prospects. In this case, the benefits of exploring the commonality along technological links are likely to be greater for these firms. We investigate this issue in this section.

In particular, we use five firm characteristics to proxy for uncertainty in a firm's prospect. The first proxy is firm size measured by the firm's total assets. Smaller firms generally face higher uncertainty, because smaller firms have fewer resources to cope with shocks in their economic environment. Our second proxy is firm age measured by the number of years the firm is covered by the CRSP. Younger firms are likely to have fewer trackable records and face more uncertainty in their business prospects. The third proxy is the ratio of retained earnings to total shareholder's equity (*RE/TE*). DeAngelo, DeAngelo, and Stulz (2006) argue that *RE/TE* captures the lifecycle stage of a firm, with a higher value of RE/TE indicating a more mature firm that relies less on external capital. More mature firms tend to have more established records of profitability and be more capable to withstand unexpected shocks. The fourth proxy is the stock return volatility, which is measured by the standard deviation of the firm's monthly stock returns in the past twelve months. High stock return volatility is generally associated with high operating and financing risks. The last proxy is the indicator of incurring an earnings loss. Firms that fail to make profits are likely to face more uncertainty. In sum, we expect that small, young firms with a low RE/TE ratio, high stock return volatility, and net losses face relatively high uncertainty.

We report the empirical results in Table 8. Except for the indicator of incurring a loss, we construct conditional variables according to the sample medians of the proxies, with the conditional variables equal to one if the value of the corresponding variable is above the sample median, and zero otherwise. For the sake of brevity, we do not report the coefficients on the control variables, and only report the coefficients on the aforementioned conditional variables, the measures of firm level technological links, and the interactions between them.

Panel A of Table 8 presents empirical evidence of how the information uncertainty affect the positive correlation between technological links and analyst coverage. In columns (1) – (2), (3) – (4), (5) – (6), (7) – (8), and (9) – (10), we use firm size, firm age, RE/TE, stock return volatility, and the loss indictor as the proxies for information uncertainty, respectively. For each of the proxies, we first examine (in columns (1), (3), (5), (7), and (9)) its interaction with

Aggregate Technological Proximity, and then examine (in columns (2), (4), (6), (8), and (10)) its interactions with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. The latter ensure that the cross-sectional variations in the positive correlation are not entirely driven by within-industry technological links.

Consistent with our expectations, the coefficients on the interaction terms between the conditional variables and *Aggregate Technological Proximity* are statistically significant and the signs of the coefficients suggest that the positive correlation between technological links and analyst coverage is more pronounced for firms associated with higher information uncertainty. Furthermore, when we replace *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*, the coefficients on the interaction terms between the conditional variables and *Across-Industry Aggregate Technological Proximity* remain statistically significant and have the expected signs.

Panel B reports empirical evidence on how the information uncertainty associated with a firm affect the positive correlation between technological links and analysts' forecast accuracy. Columns (1), (3), (5), (7), and (9) show that the coefficients on the interaction terms between the conditional variables and *Aggregate Technological Proximity* are statistically significant and have the expected signs, suggesting that the positive relationship between technological links and forecast accuracy is more pronounced for firms associated with higher information uncertainty. In columns (2), (4), (6), (8), and (10), we replace *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. We find that the coefficient estimates on the interaction terms between the conditional variables and *Across-Industry Aggregate Technological Proximity* remain statistically significant and have the expected signs.

In sum, the results in Table 8 suggest that the positive relationships between technological links and both analyst coverage and forecast accuracy are more pronounced if the firm is associated with greater information uncertainty. Furthermore, these cross-sectional variations in the positive relationships are not only driven by within-industry technological links, but are also attributable to the across-industry technological links. These results support the notion that exploring the commonality along technological links helps analysts to mitigate information uncertainty and at least partially overcome the costs of information production.

7. The Relationship between Analysts' Industry Specialization and Technological Expertise

Research shows that an analyst's industry specialization is an important determinant of the analyst's coverage decisions and forecast performance. We are interested in the question of whether there is a complementary or substitutive relationship between analysts' industry specialization and technological expertise. For this purpose, we add an interaction term between analysts' industry expertise (*pInd*) and the proxies for technological links to Models (2) and (3) in Table 5 for the determinants of analysts' continual coverage, and to Models (2), (3), (5), and (6) in Table 7 for the determinants of analysts' forecast performance, both at the firm-analyst level.

Table 9 presents the results. We do not report the coefficients for the other control variables. Columns (1) and (2) of Table 9 report the logit regression results at the firm-analyst level for whether an analyst continues to cover a firm. We find that the coefficients on analysts' industry expertise *pInd* and on the three proxies for technological links, namely, *Aggregate Technological Proximity, Within-Industry Aggregate Technological Proximity*, and *Across-Industry Aggregate Technological Proximity*, are all positive and significant as before, suggesting that analysts' industry specialization and technological expertise increase the likelihood for analysts to continue their firm coverage. The coefficient on the interaction term between *pInd* and *Aggregate Technological Proximity* in Column (1) is negative and significant, implying that to a certain degree, technological expertise substitute analysts' industry specialization for analysts' coverage decisions.

In Column (2) we replace *Aggregate Technological Proximity* with *Within-Industry Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity*. The coefficient on the interaction term of *pInd* with *Within-Industry Aggregate Technological Proximity* is insignificant, while that with *Across-Industry Aggregate Technological Proximity* is significant and negative, suggesting that analysts' technological expertise built on across-industry technological links could substitute analysts' industry specialization for their coverage decisions.

We report the OLS regression results for absolute forecast accuracy in Columns (3) and (4), and for relative forecast accuracy in Columns (5) and (6) of Table 9. We find that the coefficient on *pInd* is insignificant in Columns (3) and (4) but significantly negative in Columns (5) and (6), while the coefficients on *Aggregate Technological Proximity* and *Across-Industry Aggregate Technological Proximity* are all significantly negative. The coefficient on the interaction terms is insignificant except for that between *pInd* and *Aggregate Technological Proximity* in Column (5), where *PMAFE* is the dependent variable. Thus, the effect of technological expertise on analysts' earnings forecast accuracy is largely unaffected by analysts' industry specialization.[13]

The analysis above indicates that the effects of technological expertise on analysts' coverage decisions and forecast performance are distinct from that of industry specialization. Industry specialization allows analysts to achieve economies of scale in acquiring the relevant information within one industry, while technological expertise allows analysts to explore the informational complementarities across industries.

8. Conclusions

Little is known about analysts' coverage choices and how such choices affect their forecast performance. This paper fills this gap in the literature by relating the technological links across firms to analysts' coverage decisions and forecast performance. Using information on patents across technology classes, we measure a firm's technological links with other firms as the correlation between the firm's patent scope and the aggregate patent scope of other firms. The technological links range from zero to one, with larger values indicating greater technological similarity. To address the concern that our measures of technological links may overlap with product market similarity, we construct within-industry and across-industry

[13] To the extent that firms might have multiple segments belonging to different industries, our proxy for industry specialization could be subject to measurement errors. To mitigate this concern, we repeat our main analyses in single- and multiple-segment subsamples. Our results (untabulated) are robust in both samples.

measures of technological links based on whether a firm is from the same industry as the other firms under consideration.

We examine the effects of technological links on analysts' coverage decisions and forecast performance at both the firm level and the firm-analyst level. We find that the level of analyst coverage is positively related to a firm's technological links with other firms in the stock market, and that analysts are more likely to cover a firm with closer technological links with existing firms in their coverage portfolio. Moreover, analysts' forecast accuracy is positively related to both the firm's technological links with other firms in the stock market and its technological links with existing firms in the analysts' coverage portfolio.

We use five firm characteristics to proxy for uncertainty in the firm's prospect: firm size, age, the ratio of retained earnings to total shareholder's equity (*RE/TE*), stock return volatility, and earnings loss. We find that the positive relationships between technological links and both analyst coverage and forecast accuracy are more pronounced if the firm is associated with greater information uncertainty. We also find that such cross-sectional variations in the positive relationships between technological links and analysts' coverage and forecast performance are not only driven by within-industry but also by across-industry technological links.

We find that the effects of analysts' technological expertise on their coverage decisions and forecast accuracy are distinct from that of industry specialization. Our results suggest that the commonality along technological links allows analysts to exploit the informational complementarities across industries.

Our results corroborate the findings of Kini et al. (2009), who find that analyst specialization by country or industry is determined by the underlying common economic forces. Our findings suggest that the technological links across firms in analysts' coverage portfolios are important channels that contributes to the common economic forces. These results suggest that the commonality along technological links helps analysts mitigate information uncertainty and at least partially offset the costs of information production. Our results also corroborate the findings of Brown and Mohammad (2010) who find that analysts have not only a firm-specific but also a general ability to predict earnings. We conjecture that analysts' technology expertise is a crucial component of analysts' general ability. Our findings call for further studies on the interactions between different dimensions of analyst expertise that affect analysts' coverage choices and forecast performance.

Appendix 1: Variable definitions

Measures of Technological Proximity	
Aggregate Technological Proximity	Using information on patents across different technology classes, we construct *Aggregate Technological Proximity* to measure a firm's technological links with other firms. Similar to the bilateral technological proximity measure in Jaffe (1986), we compute a firm's *Aggregate Technological Proximity* with other firms as $\frac{S_{i,t}S'_{-i,t}}{\sqrt{S_{i,t}S'_{i,t}}\sqrt{S_{-i,t}S'_{-i,t}}}$, where the vector $S_{i,t} = (s_{i,1,t}, \ldots, s_{i,k,t}, \ldots, s_{i,K,t})$ captures the scope of technologies of firm *i*, and $S_{-i,t} = (s_{-i,1,t}, \ldots, s_{-i,k,t}, \ldots, s_{-i,K,t})$ captures the scope of technologies of firms other than firm *i*, respectively. The subscript *k* in *(1,K)* is the technology class index. The scalar $s_{i,k,t}$ ($s_{-i,k,t}$) is the ratio of the number of patents awarded to firm *i* (firms other than *i*) in technology class *k* with application years from *t-2* to *t* to the total number of patents awarded to firm *i* (firms other than *i*) applied over the same period. We construct *Aggregate Technological Proximity* at two different levels. In our firm level analyses, we compute the correlation measure between firm *i* and all other firms in our sample. In our firm-analyst level analyses, we compute the correlation measure between firm *i* and other firms covered by the analyst.
Within-Industry Aggregate Technological Proximity	This measure is the same as *Aggregate Technological Proximity*, except that $S_{-i,t}$ includes only firms that are in the same industry as firm *i*, where industries are defined by the GICS code. Similar to *Aggregate Technological Proximity*, we build this measure at both the firm level and the firm-analyst level.
Across-Industry Aggregate Technological Proximity	This measure is the same as *Aggregate Technological Proximity*, except that $S_{-i,t}$ includes only firms that are in industries different than firm *i*'s industry, where industries are defined by the GICS code. Similar to *Aggregate Technological Proximity*, we build this measure at both the firm level and the firm-analyst level.
Measures of the Scale and Scope of Firms' Technologies	
Patent Count	The number of patents the firm applied for during the three-year period from *t-2* to *t* and eventually awarded. This variable captures the scale of the firm's technological development.
Technological Concentration	Following Hirshleifer et al. (2014), *Technological Concentration* is constructed as $$Technological\ Concentration_{i,t} = \sum_{k=1}^{K}\left(\frac{n_{i,k,t}}{\sum_{k=1}^{K} n_{i,k,t}}\right)^2,$$ where $n_{i,k,t}$ is the number of patents awarded to firm *i* in technology class *k* with application years from *t-2* to *t,* and *K* is the total number of patent classes. This variable ranges between 0 and 1 and captures the scope of the firm's technologies. We also construct this variable at the analyst level in a similar way.
Measures of Analyst Activity	
$NANA_{i,t+1}$	The total number of analysts covering firm *i* in year *t+1*. An analyst is assumed to cover firm *i*, if he or she provides at least one one-year-ahead earnings forecast during year *t+1*.
$Accuracy_{i,t+1}$	The absolute forecast error in analysts' consensus, calculated as the absolute value of the

	difference between analysts' last consensus forecast and firm *i*'s actual earnings (as reported in I/B/E/S) of year t+1, deflated by the share price at the end of year *t*.
$Cover_{k,i,t+1}$	An indicator that takes the value of one if analyst *k* continues to cover firm *i* in year *t+1*.
$Add_{k,i,t+1}$	An indicator variable that takes value of one if analyst *k* initiates coverage of firm *i* in year *t+1*.
$AFE_{k,i,t+1}$	The absolute forecast error, calculated as the absolute value of the difference between analyst k's last forecast and firm i's actual earnings (as reported in I/B/E/S) for year *t+1*, deflated by the share price at the end of year *t*.
$PMAFE_{k,i,t+1}$	The proportional mean absolute forecast error, defined as the ratio of the difference between the absolute forecast error (AFE_{ijT}) by analyst i for firm j at time t and the mean absolute forecast error ($avgAFE_{jT}$) of all of the forecasts for firm j for fiscal year T, to the mean absolute forecast error $avgAFE_{jT}$, i.e., $PMAFE_{ijt}$ = (AFE_{ijT} - $avgAFE_{jT}$)/ $avgAFE_{jT}$.
Firm Level Control Variables	
$Size_{i,t}$	The natural logarithm of total assets (*#AT*) at the end of year *t*.
$MB_{i,t}$	The ratio of the market value of equity (*#CSHO* × *#PRCC_F*) to the book value of equity (*#CEQ*) at the end of year *t*.
$ROA_{i,t}$	The ratio of income before extraordinary items (*#IB*) to total assets (*#AT*) at the end of year *t*.
$Loss_{i,t}$	An indicator variable that takes the value of one if the income before extraordinary items (*#IB*) of firm *i* is negative in year *t*, and zero otherwise.
$RetVolaty_{i,t}$	The standard deviation of monthly stock returns of firm *i* in year *t*. A minimum of six months of data is required.
$Ret_{i,t}$	The cumulative monthly stock returns of firm *i*, adjusted by the value-weighted market returns, in year *t*. A minimum of six months of data is required.
$InstHold_{i,t}$	The percentage of institutional ownership of firm *i* in year *t*.
$Segm_{i,t}$	The natural logarithm of the number of segments of firm *i* in year *t*.
$MgmtFcst_{i,t}$	The natural logarithm of one plus the number of management earnings forecasts of firm *i* in year *t*.
Analyst Level Control Variables	
$Age_{k,i,t+1}$	The number of months elapsed between analyst *k*'s last forecast and the announcement of firm *i*'s earnings in year *t+1*.
$FirmExp_{k,i,t}$	The natural logarithm of one plus the number of years analyst *k* has covered firm *i* through year *t*.
$GenExp_{k,t}$	The natural logarithm of one plus the number of years analyst *k* has worked as a security analyst through year *t*.
$NCom_{k,t}$	The natural logarithm of the number of firms covered by analyst *k* in year *t*.
$NInd_{k,t}$	The natural logarithm of the number of industries covered by analyst *k* in year *t*.
$TopB_{k,t}$	An indicator variable that takes the value of one if analyst *k* is employed by a broker in the top size decile during year *t*, and zero otherwise. Size deciles are calculated based on the number of analysts employed.
$pInd_{k,i,t}$	The number of same-industry firms (other than firm *i*) in analyst *k*'s portfolio divided by the total number of firms in analyst *k*'s portfolio at year *t*.

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Table 1
Results from sampling procedures

This table presents the results from our sampling procedures.

	# obs	# firms	# analysts
Firm Level Analyses			
All COMPUSTAT/CRSP firms for Years 1990 ~ 2005	117,926	15,883	
Require firms to have common shares traded on NYSE/AMEX/NASDAQ and to have industry classification codes (GICS)	93,904	12,876	
Retain innovative firms	37,506	4,168	
Remove observations where Year *t* is Firm *i*'s final year as in COMPUSTAT	35,198	4,035	
Coverage Test (H1a)			
Remove missing values for all required variables	33,937	3,921	
Accuracy Test (H2a)			
Remove missing values for all required variables	25,965	3,426	
Analyst-Firm Level Analyses			
All one-year ahead Earnings Forecasts for Years 1990 ~ 2006	1,888,767	13,287	
Remove anonymous analysts	1,852,267	13,173	13,335
Require firms to have common shares traded on NYSE/AMEX/NASDAQ and have non-missing Actuals	1,596,026	10,132	10,829
Retain Innovative firms	888, 802	3,653	9,314
Retain analysts' final forecasts	261,213	3,653	9,314
Coverage Test (H1b)			
Remove observations where Year *t* is (a) Firm *i*'s final year as in COMPUSTAT and (b) Analyst *k*'s final year as in I/B/E/S	218,606	3,514	7,641
Remove missing values for all required variables	216,029	3,434	7,628
Accuracy Test (H2b)			
Retain observations where Analyst *k* continues or initiates coverage for Firm *i* in Year *t+1*	226,249	3,576	7,596
Remove missing values for all required variables	216,201	3,388	7,564

Table 2
Summary statistics

This table presents the summary statistics of the firm level and firm-analyst level variables. The total number of observations is 33,937 for Panel A. Subscript *i* refers to firm, *t* refers to year, and *k* refers to analyst. All continuous variables are winsorized at the 1st and 99th percentile.

Panel A: Firm level variables

Variable	N	MEAN	STD	P25	P50	P75
$NANA_{i,t+1}$	33,937	6.921	8.326	1	4	10
$Accuracy_{i,t+1}$	26,306	0.016	0.041	0.001	0.003	0.010
Aggregate Technological Proximity$_{i,t}$	33,937	0.089	0.108	0	0.049	0.143
Within-Industry Aggregate Technological Proximity$_{i,t}$	33,937	0.197	0.261	0	0.066	0.326
Across-Industry Aggregate Technological Proximity$_{i,t}$	33,937	0.072	0.087	0	0.039	0.118
Patent Count$_{i,t}$	33,937	29.355	105.819	0	2	10
Technological Concentration$_{i,t}$	33,937	0.357	0.371	0	0.25	0.556
$Size_{i,t}$	33,937	5.391	2.201	3.791	5.158	6.824
$MB_{i,t}$	33,937	3.372	4.728	1.298	2.171	3.856
$ROA_{i,t}$	33,937	-0.054	0.269	-0.056	0.030	0.075
$Loss_{i,t}$	33,937	0.342	0.474	0	0	1
$RetVolaty_{i,t}$	33,937	0.156	0.099	0.087	0.131	0.196
$Ret_{i,t}$	33,937	0.068	0.653	-0.316	-0.054	0.247
$InstHold_{i,t}$	33,937	0.404	0.269	0.167	0.385	0.619
$Segm_{i,t}$	33,937	0.462	0.637	0	0	1.099
$MgmtFcst_{i,t}$	33,937	0.307	0.565	0	0	0.693

Panel B: Firm-analyst level variables

Variable	N	MEAN	STD	P25	P50	P75
$Cover_{k,i,t+1}$	216,029	0.767	0.423	1	1	1
$Add_{k,i,t+1}$	251,668	0.202	0.401	0	0	0
$AFE_{k,i,t+1}$	216,201	0.008	0.017	0.001	0.002	0.006
Aggregate Technological Proximity$_{k,i,t}$	216,201	0.247	0.302	0	0.089	0.461
Within-Industry Aggregate Technological Proximity$_{k,i,t}$	216,201	0.233	0.316	0	0	0.457
Across-Industry Aggregate Technological Proximity$_{k,i,t}$	216,201	0.116	0.209	0	0	0.144
Technological Concentration$_{k,i,t}$	216,201	0.161	0.199	0.040	0.091	0.201
$Age_{k,i,t}$	216,201	4.063	3.153	2	3	6
$GenExp_{k,t}$	216,201	5.644	4.749	2	4	9
$FirmExp_{k,i,t}$	216,201	2.247	3.301	0	1	3
$NCom_{k,i,t}$	216,201	15.738	11.675	9	13	19
$NInd_{k,t}$	216,201	3.957	3.209	2	3	5
$pInd_{k,i,t}$	216,201	0.441	0.341	0.083	0.458	0.774
$TopB_{k,t}$	216,201	0.529	0.499	0	1	1

Table 3
Analyst forecast accuracy sorted by technological links and industry expertise

This table shows analysts' relative forecast performance on the two-way sort of technological links and industry expertise based on the median cutoff values of the final firm-analyst level sample. ∗, ∗∗, and ∗∗∗ represent significance at 10%, 5%, and 1% (two-sided), respectively.

$pInd_{k,i,t}$	Median			Mean		
	Aggregate Technological Proximity			*Aggregate Technological Proximity*		
	High	**Low**	**difference**	**High**	**Low**	**difference**
High	-0.308	-0.267	-0.041***	-0.067	-0.053	-0.014**
N	49,259	58,842		49,259	58,842	
Low	-0.241	-0.136	-0.105***	0.031	0.070	-0.039***
N	29,121	78,979		29,121	78,979	
difference	-0.067***	-0.131***		-0.098***	-0.123***	

Table 4
Analyst coverage at the firm level

This table presents the negative binomial regression results of analyst coverage at the firm level. Subscript i refers to firm and t refers to year. Variable definitions are described in Appendix 1. Year dummies are included. All continuous variables are winsorized at the 1st and 99th percentile. The t-values in parentheses are based on standard errors that are heteroskedasticity-consistent and clustered at the firm level. $*$, $**$, and $***$ represent significance at 10%, 5%, and 1% (two-sided), respectively.

Dep. Variable: $NANA_{i,t+1}$	Full sample			$NANA_{i,t+1}$>0		
	(1)	(2)	(3)	(4)	(5)	(6)
$Size_{i,t}$	0.424***	0.408***	0.403***	0.344***	0.333***	0.329***
	(61.36)	(56.36)	(55.81)	(64.89)	(60.78)	(60.06)
$MB_{i,t}$	0.043***	0.040***	0.039***	0.037***	0.035***	0.034***
	(19.17)	(18.37)	(17.90)	(18.96)	(18.56)	(18.04)
$ROA_{i,t}$	0.100**	0.134***	0.162***	0.098**	0.113***	0.135***
	(1.98)	(2.69)	(3.24)	(2.33)	(2.71)	(3.23)
$Loss_{i,t}$	-0.007	-0.050**	-0.054***	0.005	-0.025	-0.028*
	(-0.33)	(-2.49)	(-2.71)	(0.33)	(-1.47)	(-1.69)
$RetVolaty_{i,t}$	1.776***	1.462***	1.536***	1.723***	1.464***	1.532***
	(16.89)	(14.01)	(14.78)	(18.96)	(16.41)	(17.21)
$Ret_{i,t}$	0.077***	0.083***	0.082***	0.024***	0.030***	0.030***
	(8.41)	(9.19)	(9.12)	(3.15)	(3.94)	(3.94)
$InstHold_{i,t}$	1.310***	1.278***	1.290***	0.682***	0.670***	0.681***
	(28.93)	(28.28)	(28.72)	(19.50)	(19.13)	(19.65)
$Segm_{i,t}$	-0.291***	-0.279***	-0.268***	-0.181***	-0.181***	-0.172***
	(-17.29)	(-16.72)	(-16.21)	(-13.42)	(-13.56)	(-13.00)
$MgmtFcst_{i,t}$	0.140***	0.137***	0.142***	0.066***	0.064***	0.067***
	(9.23)	(9.21)	(9.48)	(5.26)	(5.17)	(5.43)
Log Patent Count$_{i,t}$		-0.012	-0.023***		-0.005	-0.014**
		(-1.47)	(-2.85)		(-0.72)	(-1.98)
Technological Concentration$_{i,t}$		0.093***	0.043**		0.026	-0.015

		(4.64)	(2.11)		(1.51)	(-0.89)
Aggregate Technological Proximity$_{i,t}$		1.318***			0.839***	
		(12.60)			(8.95)	
Within-Industry Aggregate Technological Proximity$_{i,t}$			0.480***			0.358***
			(12.48)			(10.80)
Across-Industry Aggregate Technological Proximity$_{i,t}$			0.750***			0.385***
			(6.10)			(3.54)
Constant	-1.453***	-1.428***	-1.405***	-0.492***	-0.460***	-0.443***
	(-29.96)	(-28.63)	(-28.28)	(-13.04)	(-11.98)	(-11.61)
Observations	33,937	33,937	33,937	25,839	25,839	25,839
Pseudo R^2	0.151	0.155	0.157	0.146	0.150	0.151

Table 5
Analyst coverage at the firm-analyst level

This table presents the logit regression results (Columns 1-3) and conditional logit regression results (Columns 4-6) for analyst coverage at the firm-analyst level. Subscript *i* refers to firm, *t* refers to year, and *k* refers to analyst. Variable definitions are described in Appendix 1. Year dummies are included in Columns 1-3. All continuous variables are winsorized at the 1st and 99th percentile. In Columns 1-3, the *t*-values in parentheses are based on standard errors that are heteroskedasticity-consistent and clustered at the firm and analyst level. In Columns 4-6, standard errors are clustered at the sample-firm-analyst pair level. $*$, $**$, and $***$ represent significance at 10%, 5%, and 1% (two-sided), respectively.

Dep. Variable:	$Cover_{k,i,t+1}$			$Add_{k,i,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Size_{i,t}$	0.046***	0.043***	0.042***	0.490***	0.472***	0.470***
	(6.07)	(5.57)	(5.50)	(29.44)	(27.85)	(27.74)
$MB_{i,t}$	0.009***	0.006**	0.006**	0.045***	0.043***	0.043***
	(3.62)	(2.51)	(2.51)	(35.77)	(33.44)	(33.34)
$ROA_{i,t}$	0.566***	0.572***	0.601***	0.007	0.057	0.070
	(7.81)	(7.91)	(8.30)	(0.14)	(1.08)	(1.33)
$Loss_{i,t}$	-0.105***	-0.125***	-0.127***	-0.159***	-0.177***	-0.176***
	(-4.00)	(-4.77)	(-4.85)	(-8.68)	(-9.52)	(-9.46)
$RetVolaty_{i,t}$	0.155	0.025	0.004	0.645***	0.490***	0.499***
	(0.90)	(0.15)	(0.02)	(7.11)	(5.33)	(5.43)
$Ret_{i,t}$	0.195***	0.201***	0.201***	0.212***	0.220***	0.219***
	(11.11)	(11.38)	(11.39)	(23.39)	(23.83)	(23.79)
$InstHold_{i,t}$	0.386***	0.385***	0.375***	0.426***	0.438***	0.437***
	(8.27)	(8.32)	(8.12)	(14.67)	(14.91)	(14.87)
$Segm_{i,t}$	0.015	0.018	0.020	-0.177***	-0.161***	-0.160***
	(0.94)	(1.14)	(1.23)	(-17.86)	(-16.05)	(-15.96)
$MgmtFcst_{i,t}$	0.020	0.018	0.019	0.069***	0.074***	0.076***
	(1.20)	(1.09)	(1.13)	(6.09)	(6.52)	(6.66)
$NCom_{k,i,t}$	-0.002	-0.002	-0.003			
	(-0.91)	(-0.91)	(-1.08)			
$FirmExp_{k,i,t}$	0.017***	0.016***	0.015***			
	(4.45)	(4.17)	(4.02)			
$pInd_{k,i,t}$	0.846***	0.782***	0.843***			
	(21.92)	(20.20)	(20.72)			
Log Patent Count$_{i,t}$		-0.018***	-0.016**		-0.046***	-0.045***
		(-2.68)	(-2.40)		(-9.55)	(-9.38)
Technological Concentration$_{k,t}$		-0.075	-0.062			
		(-1.44)	(-1.20)			
Aggregate Technological Proximity$_{k,i,t}$		0.360***			1.676***	
		(8.17)			(53.05)	
Within-Industry Aggregate Technological Proximity$_{k,i,t}$			0.136***			1.257***
			(3.31)			(38.67)
Across-Industry Aggregate			0.435***			1.335***

Technological Proximity$_{k,i,t}$			(7.79)			(28.23)
Constant	0.377***	0.421***	0.414***			
	(4.56)	(5.09)	(5.02)			
Observations	216,029	216,029	216,029	220,046	220,046	220,046
Pseudo R^2	0.036	0.037	0.037	0.028	0.051	0.051

Table 6
Forecast accuracy at the firm level

This table presents the OLS regression results for analyst forecast accuracy at the firm level. Subscript *i* refers to firm and *t* refers to year. Variable definitions are described in Appendix 1. Year dummies are included. All continuous variables are winsorized at the 1st and 99th percentile. The *t*-values in parentheses are based on standard errors that are heteroskedasticity-consistent and clustered at the firm level. $*$, $**$, and $***$ represent significance at 10%, 5%, and 1% (two-sided), respectively.

	Dep. Variable: $Accuracy_{i,t+1}$*100		
	(1)	(2)	(3)
$Size_{i,t}$	-0.170***	-0.146***	-0.140***
	(-10.38)	(-8.48)	(-8.11)
$MB_{i,t}$	-0.096***	-0.091***	-0.090***
	(-12.38)	(-11.71)	(-11.47)
$ROA_{i,t}$	-1.319***	-1.401***	-1.432***
	(-4.90)	(-5.25)	(-5.37)
$Loss_{i,t}$	0.996***	1.059***	1.060***
	(8.94)	(9.41)	(9.41)
$RetVolaty_{i,t}$	1.952***	2.473***	2.392***
	(4.06)	(5.04)	(4.90)
$Ret_{i,t}$	-0.635***	-0.645***	-0.644***
	(-15.31)	(-15.55)	(-15.54)
$InstHold_{i,t}$	-2.142***	-2.090***	-2.106***
	(-15.66)	(-15.36)	(-15.43)
$Segm_{i,t}$	0.211***	0.205***	0.200***
	(4.96)	(4.82)	(4.68)
$MgmtFcst_{i,t}$	-0.045	-0.042	-0.043
	(-1.05)	(-0.99)	(-1.01)
Log Patent Count$_{i,t}$		0.004	0.014
		(0.21)	(0.67)
Technological Concentration$_{i,t}$		-0.059	-0.008
		(-0.75)	(-0.10)
Aggregate Technological Proximity$_{i,t}$		-2.033***	
		(-6.20)	
Within-Industry Aggregate Technological Proximity$_{i,t}$			-0.480***
			(-3.90)
Across-Industry Aggregate Technological Proximity$_{i,t}$			-1.687***
			(-4.44)
Constant	3.133***	3.064***	3.051***
	(20.50)	(19.10)	(19.01)
Observations	25,965	25,965	25,965
Adjusted R^2	0.134	0.137	0.137

Table 7
Forecast accuracy at the firm-analyst level

This table presents the OLS regression results for absolute forecast accuracy (Columns 1-3) and relative forecast accuracy (Columns 4-6) at the firm-analyst level. Subscript *i* refers to firm, *t* refers to year, and *k* refers to analyst. Variable definitions are described in Appendix 1. Year dummies are included in Columns 1-3; all independent variables are mean-adjusted in Columns 4-6. All continuous variables are winsorized at the 1st and 99th percentile. In Columns 1-3, the *t*-values in parentheses are based on standard errors that are heteroskedasticity-consistent and clustered at the firm and analyst level. In Columns 4-6, the standard errors are heteroskedasticity-consistent. ∗, ∗∗, and ∗∗∗ represent significance at 10%, 5%, and 1% (two-sided), respectively.

Dep. Variable:	$AFE_{k,i,t+1}$*100			$PMAFE_{k,i,t+1}$ (*Independent Variables are Mean-Adjusted*)		
	(1)	(2)	(3)	(4)	(5)	(6)
$Size_{i,t}$	-0.041***	-0.041***	-0.041***			
	(-3.89)	(-3.88)	(-3.86)			
$MB_{i,t}$	-0.041***	-0.040***	-0.040***			
	(-14.16)	(-13.84)	(-13.78)			
$ROA_{i,t}$	-1.132***	-1.142***	-1.162***			
	(-7.94)	(-8.01)	(-8.10)			
$Loss_{i,t}$	0.454***	0.457***	0.458***			
	(9.31)	(9.36)	(9.38)			
$RetVolaty_{i,t}$	2.230***	2.252***	2.267***			
	(9.00)	(9.09)	(9.15)			
$Ret_{i,t}$	-0.280***	-0.282***	-0.282***			
	(-13.21)	(-13.30)	(-13.30)			
$InstHold_{i,t}$	-0.661***	-0.668***	-0.664***			
	(-11.68)	(-11.85)	(-11.80)			
$Segm_{i,t}$	0.061***	0.056***	0.055***			
	(2.92)	(2.67)	(2.64)			
$MgmtFcst_{i,t}$	-0.060***	-0.061***	-0.061***			
	(-2.89)	(-2.94)	(-2.96)			
Log Patent Count$_{i,t}$	-0.020**	-0.011	-0.011			
	(-2.50)	(-1.31)	(-1.33)			
$Age_{k,i,t+1}$	0.120***	0.120***	0.120***	0.176***	0.176***	0.176***
	(32.38)	(32.31)	(32.35)	(143.41)	(143.20)	(143.23)
$GenExp_{k,t}$	0.002	0.001	0.002	0.000	0.000	0.000
	(1.18)	(0.91)	(1.06)	(0.24)	(0.50)	(0.62)
$FirmExp_{k,i,t}$	0.006***	0.006***	0.007***	-0.009***	-0.008***	-0.008***
	(2.78)	(3.01)	(3.17)	(-10.55)	(-8.59)	(-8.51)
$NCom_{k,t}$	-0.000	-0.000	0.000	0.001***	0.002***	0.002***
	(-0.44)	(-0.16)	(0.09)	(4.66)	(7.89)	(8.00)
$NInd_{k,t}$	0.006	0.003	0.003	0.006***	-0.001	-0.001
	(1.48)	(0.70)	(0.72)	(5.91)	(-1.27)	(-1.17)
$TopB_{k,t}$	-0.033**	-0.033***	-0.030**	-0.045***	-0.035***	-0.034***

	(-2.56)	(-2.60)	(-2.32)	(-9.51)	(-7.18)	(-7.10)
$pInd_{k,i,t}$		0.003	-0.028		-0.156***	-0.163***
		(0.08)	(-0.87)		(-14.64)	(-14.96)
Technological Concentration$_{k,t}$		-0.092**	-0.098***		0.021	0.019
		(-2.53)	(-2.69)		(1.62)	(1.51)
Aggregate Technological Proximity$_{k,i,t}$		-0.129***			-0.046***	
		(-3.42)			(-3.24)	
Within-Industry Aggregate Technological Proximity$_{k,i,t}$			-0.036			-0.015
			(-0.89)			(-1.09)
Across-Industry Aggregate Technological Proximity$_{k,i,t}$			-0.220***			-0.055***
			(-5.11)			(-3.96)
Constant	1.365***	1.394***	1.398***	-0.000	-0.000	-0.000
	(13.84)	(14.12)	(14.16)	(-0.00)	(-0.00)	(-0.00)
Observations	216,201	216,201	216,201	216,201	216,201	216,201
Adjusted R^2	0.173	0.173	0.173	0.221	0.222	0.222

Table 8

Cross-sectional variations in the effects of technological links on analyst coverage and forecast accuracy

This table presents the regression results for coverage decision (Panel A) and absolute forecast accuracy (Panel B) at the firm level. Subscript *i* refers to firm and *t* refers to year. Variable definitions are described in Appendix 1. We use firm size, firm age, RE/TE, stock return volatility, and the loss indicator as proxies for the information uncertainty associated with the firm. Except for the indicator of incurring a loss, we construct conditional variables according to the sample medians of the proxies, with the conditional variables equal to one if the value of the corresponding variable is above the sample median, and zero otherwise. All of the control variables are omitted for reporting purposes. The *t*-values in parentheses are based on standard errors that are heteroskedasticity-consistent and clustered at the firm and analyst level. ∗, ∗∗, and ∗∗∗ represent significance at 10%, 5%, and 1% (two-sided), respectively.

Panel A: Analyst coverage

	Firm Size (*Cond. Var.=1 for large firms)*		Firm Age (*Cond. Var. = 1 for old firms)*		RE/TE (*Cond. Var. = 1 for mature firms)*		Stock Return Volatility (*Cond. Var. = 1 for high-volatility firms)*		Loss (*Cond. Var. = 1 for firms with loss)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Aggregate Technological Proximity$_{k,i,t}$ (A)	1.807*** (12.66)		1.333*** (11.06)		1.374*** (11.53)		0.839*** (6.93)		0.935*** (8.23)	
Within-Industry Aggregate Technological Proximity $_{k,i,t}$ (B)		0.615*** (10.78)		0.400*** (8.95)		0.483*** (10.59)		0.416*** (8.79)		0.353*** (7.87)
Across-Industry Aggregate Technological Proximity $_{k,i,t}$ (C)		1.105*** (5.63)		0.950*** (6.35)		0.882*** (5.76)		0.224 (1.53)		0.465*** (3.46)
Cond. Var.	0.151*** (4.25)	0.169*** (4.72)	-0.352*** (-12.56)	-0.345*** (-11.98)	-0.137*** (-5.20)	-0.120*** (-4.41)	0.161*** (7.83)	0.143*** (6.69)	-0.146*** (-5.57)	-0.176*** (-6.39)
Conditional Variable (A)*	-0.762*** (-4.90)		-0.285* (-1.94)		-0.295** (-2.03)		0.712*** (6.05)		0.934*** (7.15)	
Conditional Variable (B)*		-0.216*** (-3.19)		0.087 (1.31)		-0.049 (-0.74)		0.089* (1.66)		0.312*** (5.18)
Conditional Variable (C)*		-0.558** (-2.49)		-0.616*** (-2.98)		-0.421** (-2.12)		0.872*** (5.19)		0.643*** (3.58)
Constant	-1.425***	-1.408***	-1.292***	-1.269***	-1.333***	-1.319***	-1.422***	-1.388***	-1.401***	-1.374***

	(-26.78)	(-26.49)	(-27.42)	(-26.92)	(-27.23)	(-26.91)	(-27.68)	(-27.08)	(-27.92)	(-27.42)
Observations	33,937	33,937	33,937	33,937	33,887	33,887	33,937	33,937	33,937	33,937
Pseudo R^2	0.156	0.157	0.162	0.163	0.157	0.158	0.157	0.158	0.156	0.157
Panel B: Forecast accuracy										
Aggregate Technological Proximity$_{k,i,t}$ (A)	-3.082***		-2.861***		-2.854***		-0.321		0.186	
	(-6.35)		(-6.59)		(-7.09)		(-1.01)		(0.64)	
Within-Industry Aggregate Technological Proximity$_{k,i,t}$ (B)		-0.793***		-0.675***		-0.823***		0.025		0.120
		(-3.93)		(-3.97)		(-4.75)		(0.22)		(1.25)
Across-Industry Aggregate Technological Proximity$_{k,i,t}$ (C)		-2.297***		-2.232***		-2.031***		-0.572		-0.058
		(-3.74)		(-4.07)		(-3.96)		(-1.56)		(-0.18)
Cond. Var. (A)*	2.114***		1.958***		2.136***		-2.733***		-5.352***	
	(4.41)		(4.54)		(5.13)		(-6.99)		(-9.33)	
Cond. Var. (B)*		0.656***		0.535***		0.854***		-0.867***		-1.378***
		(3.07)		(2.61)		(4.36)		(-4.50)		(-5.32)
Cond. Var. (C)*		1.288**		1.304**		0.970*		-1.755***		-3.933***
		(2.00)		(2.18)		(1.71)		(-3.12)		(-4.86)
Cond. Var.	-0.082	-0.113	0.093	0.063	-0.189**	-0.238***	0.420***	0.476***	1.607***	1.681***
	(-0.86)	(-1.15)	(1.12)	(0.72)	(-2.40)	(-2.89)	(5.15)	(5.59)	(11.28)	(11.34)
Constant	3.228***	3.232***	3.086***	3.092***	3.176***	3.194***	2.903***	2.870***	2.948***	2.935***
	(18.74)	(18.66)	(18.75)	(18.64)	(18.79)	(18.82)	(18.35)	(18.15)	(18.68)	(18.57)
Observations	25,965	25,965	25,965	25,965	25,920	25,920	25,965	25,965	25,965	25,965
Adjusted R^2	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.139	0.142	0.142

Table 9

The relationship between analysts' industry specialization and technological expertise

This table presents the regression results for coverage decision in Columns (1) and (2), absolute forecast accuracy in Columns (3) and (4), and relative forecast accuracy in Columns (5 and (6), all at the firm-analyst level. Subscript *i* refers to firm, *t* refers to year, and *k* refers to analyst. Variable definitions are described in Appendix 1. All of the control variables are omitted for reporting purposes. The *t*-values in parentheses are based on standard errors that are heteroskedasticity-consistent and clustered at the firm and analyst level. $*$, $**$, and $***$ represent significance at 10%, 5%, and 1% (two-sided), respectively.

	Cover		AFE		PMAFE	
	(1)	(2)	(3)	(4)	(5)	(6)
$pInd_{k,i,t}$	0.889***	0.904***	-0.008	-0.019	-0.153***	-0.162***
	(20.25)	(20.60)	(-0.21)	(-0.54)	(-14.35)	(-14.71)
Aggregate Technological Proximity$_{k,i,t}$ *(A)*	0.612***		-0.152**		-0.036**	
	(8.50)		(-2.42)		(-2.55)	
Within-Industry Aggregate Technological Proximity$_{k,i,t}$ *(B)*		0.136*		0.012		-0.010
		(1.91)		(0.19)		(-0.73)
Across-Industry Aggregate Technological Proximity$_{k,i,t}$ *(C)*		0.796***		-0.266***		-0.055***
		(11.21)		(-3.75)		(-3.94)
$pInd_{k,i,t}$*(A)*	-0.499***		0.045		0.114**	
	(-4.50)		(0.49)		(2.38)	
$pInd_{k,i,t}$*(B)*		0.075		-0.102		0.037
		(0.64)		(-1.17)		(0.82)
$pInd_{k,i,t}$*(C)*		-0.883***		0.097		0.067
		(-6.21)		(0.87)		(1.19)
Constant	0.407***	0.408***	1.396***	1.398***	-0.001	-0.000
	(4.93)	(4.95)	(14.16)	(14.19)	(-0.61)	(-0.15)
Observations	216,029	216,029	216,201	216,201	216,201	216,201
Pseudo R^2 / Adjusted R^2	0.037	0.038	0.173	0.173	0.222	0.222