Analysts' Site Visits and Corporate Innovation*

Qiang Cheng
Singapore Management University

Yutao Wang
Renmin University of China

Holly Yang
Singapore Management University

Zheyuan Zhang
Renmin University of China

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Abstract

While prior studies examine whether analyst coverage affects corporate innovation, there is little research on the mechanism through which financial analysts affect corporate innovation. In this paper, we examine whether and how analysts' questions about innovation affect corporate innovation activities and outcomes. Using a sample of corporate site visits in China, we find that when analysts ask questions about innovation during site visits, the firms invest more in research and development and file more patent applications in the future. This association is stronger when analysts have a greater information and monitoring role. In addition, consistent with knowledge diffusion between firms, analysts' questions have a stronger effect when there is more technical spillover potential in the industry. However, the effect is weakened when managers feel pressure to reduce investment in innovation to meet capital markets' earnings expectations. Overall, we provide evidence that analysts play a direct role in corporate innovation through their questioning of firms' innovation activities.

Key words: Analyst coverage, site visits, innovation, R&D expenditures

JEL codes: G30, M40, O33

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1. Introduction

Innovation is an important long-term investment for firms. However, investing in innovation activities is risky and has uncertain benefits (e.g., Holmstrom 1989; Scherer and Ross 1990). Agency theory predicts that risk-averse managers do not undertake the optimal amount of investment in corporate innovation (Jensen and Meckling 1976). In addition, because of information asymmetry regarding corporate innovation, capital markets might not fully incorporate the potential benefits of investing in corporate innovation, reducing firm value and increasing the likelihood of firms being hostile takeover targets (e.g., Stein 1988). As a result of these market frictions, it is likely that firms underinvest in corporate innovation, investing instead in less risky projects for short-term profits at the expense of long-term value. Consequently, how firms can be motivated to invest in corporate innovation is an important question. Of particular interest is the role played by financial analysts. Prior studies examine whether financial analysts induce or hinder firms' investments in innovation, including both inputs, such as research and development (R&D) expenditures, and outputs, such as patents, and document mixed evidence (e.g., Derrien and Kecskes 2013; He and Tian 2013; Guo, Perez-Castrillo and Toldra-Simats 2019). In addition, there is little research on the mechanism through which analysts affect corporate innovation. This paper contributes to this line of research by investigating the mechanism through which analysts can affect corporate innovation and, more specifically, whether analysts asking questions about corporate innovation during site visits has any effect on firms' future innovation activities.

Analysts can affect corporate innovation for four nonexclusive reasons. First, they can positively affect corporate innovation via their information acquisition and dissemination role. Corporate innovation activities have high uncertain long-term benefits, but reduce earnings in the short run. In addition, firms tend not to disclose proprietary information regarding such activities. As a result, capital markets are likely to undervalue firms that undertake more innovation. Given analysts' ability to acquire and process information, they can help market participants better understand the potential benefits of innovation activities, reducing the undervaluation of such firms. Anticipating such an effect, firms covered by analysts invest more in innovation activities. We refer to this prediction as *the information hypothesis*.

Second, analysts can positively affect innovation through a corporate governance mechanism (Jensen and Meckling 1976; Healy and Palepu 2001). Because analysts often interact with management during conference calls and site visits, they can directly question whether management is investing sufficiently in R&D to enhance existing or to develop new technologies. Therefore, analysts can act as monitors by exerting pressure on managers who otherwise might underinvest in innovation. This prediction is referred to as *the monitoring hypothesis*.

Third, analysts can positively influence corporate innovation via a knowledge spillover effect. Prior research suggests that knowledge spillovers can occur from innovators to other parties, including competitors, and that the spillover effect can be facilitated by financial intermediaries (e.g., Jaffe, Trajtenberg, and Fogarty 2000; Lurong, Moshirian, Nguyen, Tian, and Zhang 2017). Analysts can facilitate knowledge spillovers regarding innovation because they usually cover several firms in the same industry and thus have information about these firms' innovation activities through their network with firm management, processing of public information, and information acquisition on innovation activities. Consistent with information flow from analysts to managers, Martens and Sextroh (2021) find that a firm is more likely to cite another firm's patents if both firms are covered by the same analyst. We refer to this as *the* *knowledge spillover hypothesis*.

Although the discussion above suggests that analysts have a positive effect on firms' innovation activities, there is a matter of debate in the literature. Specifically, the counter argument is that analysts can unintentionally negatively affect firms' innovation activities via their forecasts of quarterly and annual earnings. Capital market participants generally use analysts' earnings forecasts as market expectations, and failing to meet analysts' earnings forecasts can lead to significant stock price drops (Skinner and Sloan 2002). The pressure to meet short-term earnings forecasts can lead to managerial myopia, including underinvestment in long-term innovation activities. Consistent with this pressure effect, prior studies find that firms covered by more analysts generate fewer and less impactful patents (He and Tian 2013). This prediction is referred to as *the pressure hypothesis*.

When analysts ask questions about corporate innovation during site visits, they can better understand the level and potential benefits of corporate innovation and/or share information about industry peers' innovation activities.[1] This suggests that firms with analysts asking questions about corporate innovation during site visits will experience a greater increase in innovation activities in the future via analysts' information, monitoring, and knowledge spillover roles than will other firms. However, if analysts are more concerned about the negative effect of these investment activities on firms' short-term profits, the pressure hypothesis suggests that we will find the opposite result.

We test the predictions of these hypotheses by examining both the inputs (i.e., R&D investments) and outputs (i.e., patent applications) of innovation activities of firms with analysts' site visits. Using a sample of 7,284 firm-years in China from 2013 to 2019, we find that firms

[1] Appendix A provides examples of questions on corporate innovations from site visit transcripts that are consistent with the four hypotheses regarding the effect of analysts on corporate innovation.

increase their R&D in the following year when they are asked about innovation activities during site visits involving analyst participation. In addition, firms that are asked about innovation activities during site visits increase their patent applications in the following year. The results hold whether we use an indicator variable for firms with site visits during which the firms are asked about innovation, or the ratio of such site visits to all site visits that the firm has in a year. These results are robust to controlling for various firm characteristics associated with firms' innovation activities, as well as industry and year fixed effects. Furthermore, the effect is economically significant: compared with other firms, firms with site visits in which analysts ask innovation-related questions experience increases in R&D expenditures and patent applications of 7.2% and 8.3%, respectively, of the sample standard deviation in the following year.

Although the main results indicate a positive average effect of analysts' questions during site visits on corporate innovation, we conduct several cross-sectional tests to distinguish among the different predictions. We find evidence consistent with all four proposed channels. Specifically, consistent with the information role of analysts, we find that analysts' questions have a stronger effect when there are more analysts participating in the site visits or when there is more media coverage for the firm. Moreover, the positive effect of analysts' questions on innovation activities is stronger when the firm has higher agency costs, as captured by chief executive officer (CEO)–chairman duality and tunneling by controlling shareholders. This suggests that analysts' questions help to monitor managers' innovation activities when managers are likely to underinvest in R&D. We also find that analysts' questions help to diffuse knowledge among firms and have a more positive effect on innovation activities when the analysts cover more firms in the same industry and when the firm exhibits a greater degree of technical similarities with other firms in the same industry. Finally, we find that the positive effect of analysts' questions on corporate innovation is weaker when the CEO is close to retirement or when the firm is distressed, consistent with the pressure hypothesis.

In the main analyses, we use analysts' questions on innovation in the current year to explain *future* R&D investments and patent applications to address the confounding effect of the contemporaneous relation between the two and to address the impact of reverse causality. To further mitigate reverse causality, we restrict our sample to firms without R&D or patent activities in the prior year and obtain the same inferences. In another test, we control for whether analysts ask questions about corporate innovation in the year before and the year after our variable of interest to mitigate concerns about the endogenous relation between analysts' questions and future innovation. The inferences remain the same.

This paper contributes to the literature in several ways. First, it contributes to the innovation literature by studying analysts' direct influence on corporate innovation through their interactions with managers during site visits. Complementing research on the effect of analyst coverage on corporate innovation (Derrien and Kecskes 2013; He and Tian 2013; Guo et al. 2019; Martens and Sextroh 2021), we focus on the mechanism through which analysts can affect corporate innovation. Specifically, we show that by raising questions about firms' innovation activities, analysts can help induce managers to undertake investments that they otherwise would not have undertaken owing to the valuation problems of R&D investments or agency costs.

Second, this paper contributes to the growing literature on the real effects of financial analysts, which documents mixed evidence on whether analyst coverage is beneficial (e.g., Yu 2008; McInnis and Collins 2011; Chen, Harford, and Lin 2015; Irani and Oesch 2016; Chapman and Green 2018; To, Navone, and Wu 2018; Ayres, Campbell, Chyz, and Shipman 2019). Our paper contributes to the debate by documenting a positive effect of financial analysts on corporate innovation.[2]

Third, this paper contributes to the literature on corporate site visits, which shows that site visits are informative to capital market participants and can help analysts improve their forecast accuracy (Cheng, Du, Wang, and Wang 2016; Bowen, Dutta, Tang, and Zhu 2018; Han, Kong, and Liu 2018; Cheng, Du, Wang, and Wang 2019). We contribute to this stream of research by analyzing the content of site visit transcripts and showing that the actions taken by analysts can shape corporate innovation.

The remainder of this paper is organized as follows. Section 2 provides a review of the related literature and develops the hypotheses. Section 3 presents the sample, data, and research design. Section 4 reports the main analyses, and Section 5 presents the cross-sectional analyses. We discuss the additional analyses in Section 6 and conclude the paper in Section 7.

2. Related research and hypothesis development

2.1 Review of the related literature

Prior studies examine whether financial analysts induce or hinder firms to invest in innovation and document mixed evidence (e.g., Derrien and Kecskes 2013; He and Tian 2013; Guo et al. 2019). One of the earliest contributors to this debate, He and Tian (2013) examine the effect of analyst coverage on patenting activity. They find that compared with firms with low analyst coverage, those with high analyst coverage file fewer patents and have fewer patent citations. Their results are consistent with the "dark side" of analyst coverage and suggest a

[2] Chapman and Green (2018) show that analysts' questions about forward-looking information affect the likelihood of managers providing guidance in future periods, consistent with firms providing voluntary disclosure when there is greater demand for such information. However, it is not obvious whether analysts' questions about innovation activities have a direct and positive impact on a firm's R&D and patent applications in our setting, given that analysts do not forecast R&D expenditures or patent activities.

negative association between analyst coverage and corporate innovation. In contrast, focusing on firms with a drop in analyst coverage as a result of brokerage closures and mergers, Derrien and Kecskes (2013) find that such firms experience a decrease in R&D expenditures. This finding is consistent with that of Barth, Kasznik, and McNichols (2001), who document a positive association between analyst coverage and R&D expenditures. Gentry and Shen (2013) find that although R&D intensity decreases with a firm's performance gap (the difference between analyst earnings forecasts and actual earnings, which is a proxy for market pressure for short-term earnings), the association is weaker for firms with higher analyst coverage. More recently, examining three types of innovation activities, Guo et al. (2019) find that an increase in analyst coverage can lead to a decrease in R&D expenditures but an increase in the acquisition of innovative firms and investments in corporate venture capital. After controlling for the change in these three types of activities, Guo et al. (2019) further find that an increase in analyst coverage does not affect the number and quality of patents. Their results suggest that although analyst coverage may pressure managers to cut R&D in the short run, it leads to more investment in the long run.

Complementing these studies, which examine the association between analyst coverage and the level of corporate innovation activities, this paper examines the *actions* taken by analysts that can affect corporate innovation, that is, asking questions about corporate innovation during site visits. In doing this, we provide evidence of one mechanism through which analysts directly affect corporate innovation. Such evidence can shed light on the argument concerning how analysts affect corporate innovation through private communication with firm management.

2.2 Hypothesis development

Analysts can affect corporate innovation for four nonexclusive reasons. First, they can positively affect corporate innovation via their information role in capital markets, which is referred to as the information hypothesis. Corporate innovation activities have highly uncertain benefits and can reduce short-term profits. In addition, firms tend not to disclose proprietary information regarding such activities, exacerbating the information asymmetry surrounding corporate innovation activities. As a result, capital markets are likely to undervalue firms with more innovation activities. Given analysts' ability to acquire and process information, they can help market participants better understand the long-term benefits of innovation activities and distinguish whether poor firm fundamentals or long-term investments in innovation are driving low earnings. As such, analysts can help reduce the information asymmetry between capital market participants and managers regarding innovation activities. Then, the information about the long-term benefits can be incorporated into stock prices, reducing the potential undervaluation of firms undertaking more innovation activities, despite adverse impacts on earnings in the short term (e.g., He and Tian 2013; Zhong 2018; Guo et al. 2019). Anticipating such an effect, firms with high analyst coverage are likely to invest more in innovation activities.

In the context of site visits, analysts acquire additional information regarding corporate innovation activities when they ask questions about innovation during site visits. Analysts can report on the additional information acquired during site visits, which can be combined with other information that analysts or investors possess to shed light on the long-term benefits of innovation. For example, Ringpu Biotech hosted a site visit for analysts from Essence Securities on September 22, 2016; one of the topics discussed during the session was the development of its H5N2 subtype (strain D7 and strain rD8) inactivated influenza vaccine that had reached the review and testing phase. As the first H5 subtype inactivated influenza vaccine in China, it would help prevent influenza infection in poultry and birds.[3] This information was later reflected in the analyst report issued by Essence Securities on October 14, 2016. By acquiring and disseminating such information, analysts help reduce information asymmetry on corporate innovation and, as predicted by the information hypothesis, induce firms to invest more in innovation.

Second, analysts can positively affect corporate innovation through a corporate governance mechanism. The argument that analysts can play a monitoring role because of their expertise and comparative advantage was put forward as early as the 1970s by Jensen and Meckling (1976). However, evidence for the governance role of analysts has been limited and indirect until recently. Yu (2008) examines the association between analyst coverage and firms' earnings management behavior and finds that firms covered by more analysts manage earnings less. Using a more comprehensive set of corporate governance measures and brokerage closures as an exogenous shock, Chen et al. (2015) document that analyst coverage helps to mitigate corporate expropriation of outside shareholders.[4]

During site visits with management, analysts can directly inquire about firms' investments in innovation and patent applications because they are equipped with the background knowledge and skills to analyze information about firms' financials and operations. Executives must be prepared to answer such questions, and their answers will be incorporated into analyst reports and disseminated to capital markets. As an example of analysts' monitoring role, during a site visit on June 8, 2015, Kelun Pharmaceutical was asked whether it was lagging behind the top

[3] Since 2009, the Shenzhen Stock Exchange has required listed firms to disclose information about investor-related activities, including site visits, in their annual reports. See Appendix A for excerpts of company disclosures and corresponding analyst reports discussed in the text.
[4] Prior studies provide evidence supporting the monitoring role of analysts in other settings, such as credit ratings (Cheng and Subramanyam 2008), real earnings management (Irani and Oesch 2016), and goodwill impairment (Ayres et al. 2019).

pharmaceutical companies in R&D investments and, more specifically, behind large pharmaceutical companies, including Hengrui Medicine and Qilu Pharmaceutical, in the area of biopharmaceutical products. We predict that analysts' monitoring can reduce managerial myopia and increase corporate innovation activities, and refer to this prediction as the monitoring hypothesis.

Finally, analysts can positively affect firms' innovation activities via a knowledge spillover effect. The knowledge spillover effect is well documented in the economics literature (e.g., Cohen and Levinthal 1989; Aghion and Jaravel 2015). For example, Jaffe et al. (2000) find that knowledge spillovers can occur from innovators to other parties, including competitors. Research indicates that the spillover effect can be facilitated by financial intermediaries. For example, Lurong et al. (2017) find that foreign institutional investors can facilitate the spillover effect from high- to low-innovation economies.[5]

Analysts can facilitate knowledge spillovers regarding innovation. Usually, they cover several firms in the same industry and thus have information about these firms' innovation activities through networks with firm managers, processing of public information, and information acquisition on innovation activities. As such, analysts may have more information than a firm's managers about the innovation activities of other firms in the same industry; such information is hard to obtain given its proprietary nature and the lack of corporate disclosure on innovation activities. Consistent with this notion, Martens and Sextroh (2021) find that a firm is more likely to cite another firm's patents if both firms are covered by the same analyst. As such,

[5] Studies find that CEOs' networks can facilitate knowledge spillovers. For example, Faleye, Kovacs, and Venkateswaran (2014) find that firms with better connected CEOs invest more in R&D and file more patents than other firms, partly because better connected CEOs have better access to the relevant network.

feedback from analysts can help managers reflect on and improve their investment decisions.[6] We refer to this prediction as the knowledge spillover hypothesis.

One mechanism through which the knowledge spillover effect can affect corporate innovation is question and answer sessions with managers as part of site visits. During such sessions, analysts can share information about competitors' innovation activities. For example, during a site visit on December 28, 2016, T&S Communication was asked about its strategic plan for high-end products, given that competitors such as Accelink Technologies and InnoLight were developing 400G optical communication products. Analyst feedback may prompt firms to increase their own innovation activities owing to concerns about the enhanced competition brought about by competitors' innovation activities.

Although the discussion above suggests that analysts can positively affect innovation, analysts can also (even if unintentionally) affect firms' innovation activities negatively via their focus on quarterly or annual earnings, which we refer to as the pressure hypothesis. Capital market participants generally use analysts' earnings forecasts, including quarterly earnings forecasts, as market expectations. While meeting or beating analysts' earnings forecasts can lead to stock price increases, failing to do so can lead to significant stock price drops (e.g., Bartov, Givoly, and Hayn 2002; Skinner and Sloan 2002). Because investments in corporate innovation do not increase earnings in the short term and indeed can lead to a drop in earnings because of R&D expenditures, the pressure to meet short-term earnings forecasts can result in managerial myopia, including underinvestment in long-term innovation activities (Hazarika, Karpo, and Nahata 2012; He and Tian 2013). For example, Graham, Harvey, and Rajgopal (2005) report that

[6] Consistent with information flows from analysts to managers, Bae, Biddle, and Park (2022) find that managers' capex forecast errors are positively associated with analyst feedback and that analyst feedback is positively associated with changes in investment efficiency.

78% of the executives surveyed would sacrifice long-term value to meet short-term earnings targets.

It follows from the pressure hypothesis that when analysts ask questions about corporate innovation during site visits, some might be concerned about the negative effect of innovation activities on short-term profits due to the expensing of R&D investments. For example, during the site visit on November 30, 2018, the executives of Jiangling Motors were asked how management expected to balance the company's short- and long-term goals given its large R&D expenditures and the fact that the company had reported its first quarterly loss in 10 years. The pressure hypothesis suggests that when analysts are more concerned with the short-term negative effect rather than the long-term positive effect of innovation activities, capital market participants might undervalue firms that invest in corporate innovation activities (He and Tian 2013). As such, firms are more likely to cut innovation activities to increase short-term profits at the expense of long-term benefits when analysts ask more questions about innovation during site visits.

In summary, the competing arguments above suggest that analysts' questions about innovation during site visits can have either a positive or a negative effect on corporate innovation activities. Thus, we state our hypothesis in the null form:

H1: Analysts' questions about corporate innovation during site visits have no impact on corporate innovation activities.

We test the above hypothesis by comparing the change in corporate innovation activities between firms with and without analysts asking questions about corporate innovation.

3. Sample and research design

3.1 Sample and data

We collect data from several sources: financial data and institutional holdings data from the China Stock Market & Accounting Research database, patent data from the Chinese Research Data Services Platform, and site visit data from the WIND database. We merge these databases to create our initial sample of 47,310 site visits and 9,172 firm-years from 2,331 unique firms for the period from 2013 to 2019. After removing observations with missing values for our variables and visitor information, the final sample includes 41,257 site visits, 7,284 firm-years, and 1,851 unique firms. Table 1 provides the sample selection process. All of our analyses are conducted at the firm-year level.

[Insert Table 1]

3.2 Measurement of corporate innovation

We examine the effect of analysts' questions about firms' future innovation activities by analyzing changes in the input and output measures of corporate innovation activities. We examine both input and output measures because they complement each other (e.g., Autor, Dorn, Hanson, Pisano, and Shu 2020). Patent applications filed indicate the occurrence of innovations resulting from innovation inputs, but they can underestimate the innovation activities because some innovations might not be codified in patents (e.g., trading secrets) or important enough to be registered as patents.

We focus on the change in corporate innovation activities in year t+1 to investigate the Granger causal effect of analysts asking questions about innovation in year t. We do not examine the change in innovation activities in year t because these innovation activities may induce analysts to ask questions during site visits, leading to a spurious positive association. We examine the change in corporate innovation activities to control for the impact of firm characteristics that affect both the level of corporate innovation activities and analysts' tendency to ask questions about innovation during site visits.

Following the literature (e.g., Dai, Shen, and Zhang 2015; Guo et al. 2019), the input measure, $\Delta R\&D_{t+1}$, is the one-year-ahead change in R&D, defined as the difference between *R&D* expenditures in year *t*+1 and average *R&D* expenditures in years *t*-1 and *t*-2, scaled by average revenue in years *t*-1 and *t*-2. Then, we multiply this value by 100 for ease of interpretation. We use average R&D in years *t*-1 and *t*-2 to reduce the impact of the volatility of annual R&D expenditures.

To construct the output measure of innovation, we first calculate the change in the number of patent applications in year *t*+1 ($\Delta Patent_{t+1}$), which is calculated as the difference between the number of patent applications in year *t*+1 and the average number of patent applications in years *t*-1 and *t*-2. We use the number of patent applications in a given year, as commonly done in the literature (Guo et al. 2019).[7, 8] Then, we take the natural logarithm of this variable, $Ln\Delta Patent_{t+1}$, to address the skewness of the variable. When the change in patent applications is negative, $Ln\Delta Patent_{t+1}$ is calculated as –1 times the natural logarithm of the absolute value of the change in patent applications.

As reported in Panel A of Table 2, on average, firms increase their *R&D* by 3.1% of sales and patent applications by 13.9 in year *t*+1.

[Insert Table 2]

3.3 Measurement of analysts asking questions about corporate innovation during site visits

To capture analysts asking questions about corporate innovation during site visits, we

[7] There are three types of patents in China: invention, utility model, and design patents. We include all patents in the main analyses. In a sensitivity test, we focus on invention patents and obtain the same inferences.

[8] In contrast to the US, where information about patent applications is publicly released by the US Patent Office (USPTO) only after the grant date, in China, we can observe all patent applications. This research design mitigates concerns about truncation bias because all applications, successful or not, are included in our sample. In an untabulated analysis, we examine whether our results are robust to using only approved patent applications for a shorter sample period (i.e., 2013–2019) and find consistent results.

search keywords related to innovation in the question sections of site visit transcripts. The keywords that we use are "technology," "R&D," "science and technology," "development," "innovation," "laboratory," "research," "patent," and "invention." If the question section of a site visit transcript includes any of the keywords and at least one analyst participates in the site visit, we deem this site visit as one involving analysts asking questions about corporate innovation.[9]

Then, we use the information to construct two variables at the firm-year level: an indicator variable ($AnalystAsk\_D_{it}$) and a ratio variable ($AnalystAsk\_R_{it}$). $AnalystAsk\_D_{it}$ is an indicator variable that equals one if there is at least one site visit in which analysts participate and during which firm *i* is asked about innovation in year *t*. $AnalystAsk\_R_{it}$ is the ratio of the number of site visits in which analysists participate and during which firm *i* is asked about innovation in year *t* to the total number of site visits to firm *i* in the same year.

As reported in Panel A of Table 2, the summary statistics suggest that about 56% of the firm-years have site visits during which analysts ask innovation-related questions (*AnalystAsk_D* = 0.563). Note that all firm-years in the sample have site visits because we examine the impact of analysts asking questions about innovation during site visits conditional on the occurrence of site visits. At the firm-year level, analysts ask innovation-related questions in approximately 28% of the site visits.

3.4 Research design

We use the following regression model to investigate the impact of analysts' questions

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[9] We use the term "site visits with analysts asking questions about corporate innovation" for brevity. Because site visit transcripts do not specify who asks a specific question, we cannot determine whether it is an analyst or another site visit participant who asks the question. As such, we require at least one analyst to participate in the site visit. Even if the analyst does not ask the questions related to innovation, the analyst obtains and processes the information about corporate innovation and thus the four arguments related to the impact of analysts on corporate innovation activities apply. In an additional analysis that we report later, we examine the incremental effect of analyst participation over participation by others in site visits during which firms are asked about innovation activities.

about corporate innovation:

$$\begin{aligned}\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} \\ &= \beta_0 + \beta_1 AnalystAsk_{it} + \gamma_1 AC_{it} + \gamma_2 Size_{it} + \gamma_3 Age_{it} + \gamma_4 Leverage_{it} \\ &+ \gamma_5 Profit_{it} + \gamma_6 BM_{it} + \gamma_7 R\&D_{it} + \gamma_8 CASH_{it} + \gamma_9 PPE_{it} + \gamma_{10} CAPEX_{it} \\ &+ \gamma_{11} InstOwn_{it} + \gamma_{12} HHI_{it} + \gamma_{13} HHI_{it}^2 + \gamma_{14} KZindex_{it} + YEAR_t \\ &+ INDUSTRY_j + \varepsilon_{it+1}\end{aligned} \tag{1}$$

where subscripts *i*, *t*, and *j* refer to firm *i*, year *t*, and industry *j* to which firm *i* belongs, respectively. The dependent variable is $\Delta R\&D_{it+1}$ or $Ln\Delta Patent_{it+1}$, as defined above. The independent variable of interest is $AnalystAsk_{it}$, which is $AnalystAsk\_D_{it}$ or $AnalystAsk\_R_{it}$. The information, monitoring, and spillover effect hypotheses predict a positive coefficient on $AnalystAsk_{it}$, whereas the pressure hypothesis predicts a negative coefficient.

Following the innovation literature (He and Tian 2013; Guo et al. 2019), we control for several firm characteristics that are likely to affect innovation activities. AC_{it} is the number of analysts covering the firm, $Size_{it}$ is the natural logarithm of total assets, Age_{it} is the number of years since the creation of the firm, $Leverage_{it}$ is total liabilities divided by total assets, $Profit_{it}$ is an indicator variable that equals one if firm *i* reports a net profit in year *t* and zero otherwise, and BM_{it} is the book-to-market ratio. $R\&D_{it}$ is lagged R&D expenditures, defined as the sum of R&D in year *t*-1 and *t*-2, divided by the sum of revenues in year *t*-1 and *t*-2; we multiply this value by 100 for ease of interpretation. $CASH_{it}$ is cash divided by total assets, PPE_{it} is property, plant, and equipment divided by total assets, $CAPEX_{it}$ is capital expenditure (capex) divided by total assets, and $InstOwn_{it}$ is the ownership of institutional investors. HHI_{it} is the Herfindahl- Hirschman index for the industry to which the firm belongs. We also include HHI^2_{it} to capture the nonlinear effect of industry concentration on innovation (Aghion et al. 2005). $KZindex_{it}$ is the Kaplan–Zingales (KZ) index, which measures a firm's financial constraints. All of the control variables are measured in year *t* except for lagged R&D. Appendix B provides detailed variable definitions. We also include industry and year fixed effects to control for unobservable industry-specific or year-wide factors affecting innovation activities. To minimize the influence of outliers, we winsorize all continuous variables at the 1^{st} and 99^{th} percentiles. We calculate *t*-statistics based on standard errors adjusted for clustering at the firm level.[10]

As reported in Panel A of Table 2, an average firm has 6.6 analysts following it, a book value of assets of 9.452 billion yuan, an age of 7.9 years, leverage of 38.7%, a book-to-market ratio of 0.35, an R&D-to-revenue ratio of 0.045, a cash-to-asset ratio of 0.162, a PPE-to-asset ratio of 0.198, a capital expenditure-to-asset ratio of 0.052, institutional ownership of 38.56%, and a KZ index of 1.312. In addition, the average Herfindahl index at the industry level is 0.087.

Panel B of Table 2 reports the correlations between the variables used in the main analyses. The magnitudes of the correlation coefficients are generally small, except those between *Size* and *Age* (0.545 for the Pearson correlation), *Size* and *Leverage* (0.563), *Size* and *BM* (0.499), *Leverage* and *KZindex* (0.682), and *HHI* and HHI^2 (0.883). A variance inflation factor (VIF) analysis indicates that there is no multicollinearity problem.

4. Main analyses

Table 3 reports the results of the analysis of $\Delta R\&D_{t+1}$. In Column (1), we find that the coefficient on $AnalystAsk\_D_{it}$ is 0.409 and significantly positive at the 1% level. This result is consistent with analysts' innovation-related questions being positively associated with an increase in R&D expenditures in the following year. The effect is not only statistically significant but also economically significant. The magnitude of the coefficient indicates that compared with other firms, firms with site visits in which analysts ask innovation-related

[10] The inferences remain the same when we calculate *t*-statistics based on Huber–White standard errors.

questions experience an increase in R&D expenditures of 0.409% of sales in the following year, or a relative increase of 7.2% (= 0.409/5.642) of the sample standard deviation of $\Delta R\&D_{t+1}$. Note that because the change in R&D can be negative or positive, we use the standard deviation, instead of the sample mean, to gauge the economic significance of the results. The results using the ratio variable presented in Column (2) are similar. Specifically, we find that the coefficient on $AnalystAsk\_R_{it}$ is significantly positive at the 1% level.

[Insert Table 3]

In terms of control variables, we find that the one-year-ahead change in R&D is positively associated with *AC*, *Size*, *Leverage*, *Profit*, *BM*, *R&D*, and *CAPEX*, and is negatively associated with *CASH*, *PPE*, *HHI*, and *KZindex*.

Table 4 reports the results of the analysis of $LnPatent_{t+1}$. In Column (1), we find that the coefficient on $AnalystAsk\_D_{it}$ is 0.234 and significantly positive at the 1% level. This result is consistent with analysts' innovation-related questions being positively associated with an increase in patent applications in the following year. Again, the effect is not only statistically significant but also economically significant. The magnitude of the coefficient indicates that compared with other firms, firms with site visits in which analysts ask innovation-related questions experience an increase in the number of patent applications of 8.3% (= 0.234/2.830) of the sample standard deviation in the following year. The results using the ratio variable presented in Column (2) are similar: we find that the coefficient on $AnalystAsk\_R_{it}$ is significantly positive at the 5% level.

[Insert Table 4]

In terms of control variables, we find that the one-year-ahead change in patent applications is positively associated with *AC*, *Size*, *Leverage*, *Profit*, *BM*, and *CAPEX*, and is negatively associated with *Age* and *KZindex*.

Overall, the results in Tables 3 and 4 suggest that analysts' questions about firms' innovation-related activities are associated with an increase in both the input and output of corporate innovation. These results are consistent with the information hypothesis, the monitoring hypothesis, and the spillover effect hypothesis.

5. Cross-sectional analyses

In this section, we conduct several cross-sectional tests to distinguish among the four hypotheses: i) the information hypothesis, ii) the monitoring hypothesis, iii) the knowledge spillover hypothesis, and iv) the pressure hypothesis. For brevity, we only discuss and tabulate the results using the indicator variable of $AnalystAsk_{it}$ in this section. The results are qualitatively similar when we use $AnalystAsk\_R_{it}$ in the cross-sectional analyses.

5.1 Information hypothesis

If managers anticipate that analysts help reduce the undervaluation problem arising from R&D investments and thus engage in more innovation activities, then the results should be stronger when analysts can better disseminate information about firms' innovation activities. Prior studies find that site visits are more informative and can better enhance analysts' forecast accuracy when there are more analysts attending the site visit (e.g., Cheng, Du, Wang, and Wang 2016). Moreover, Ahn, Drake, Kyung, and Stice (2019) find that media coverage of analysts' reports results in market participants being better informed of analysts' recommendation revisions, suggesting a complementary role between financial analysts and the business press. Therefore, the effect should be stronger when there is greater media coverage of the firm, further disseminating the information acquired by analysts during site visits. As such, we construct two variables, $AnalystNum_{it}$ and $NewsCov_{it}$, to explore the information role of analysts. $AnalystNum_{it}$ is an indicator variable that equals one if the average number of analysts participating in site visits during which the firm is asked about innovation exceeds the sample median, and zero otherwise. $NewsCov_{it}$ is an indicator variable that equals one if the number of news reports about the firm is above the sample median, and zero otherwise. Then, we add the interaction terms of $AnalystAsk\_D_{it}$ with $AnalystNum_{it}$ and $NewsCov_{it}$ to the regression model and expect a positive coefficient on the interaction terms if our main results are at least partially driven by the information role of analysts.

Table 5 presents the results of this analysis. We first discuss the results using $AnalystNum_{it}$ in Panel A. Consistent with the information role of analysts, we find that the coefficient on $AnalystAsk\_D_{it} \times AnalystNum_{it}$ is positive and significant at the 1% level for the analysis of the change in R&D expenditures.[11] In Panel B, where we use $NewsCov_{it}$, we find significantly positive coefficients on $AnalystAsk\_D_{it} \times NewsCov_{it}$. The coefficient on $AnalystAsk\_D_{it} \times NewsCov_{it}$ is significant at the 1% level in the analysis of both the change in R&D and the change in patent applications.

[Insert Table 5]

Overall, these results are consistent with the information hypothesis and suggest that analysts' questions have a positive effect on corporate innovation through their information role in capital markets.

5.2 Monitoring hypothesis

Next, we examine whether analysts' questions help induce managers to engage in more innovation activities as a result of the monitoring role of analysts. The monitoring hypothesis

[11] The main effect of $AnalystNum_{it}$ is omitted because it is coded as zero by default when $AnalystAsk\_D_{it}$ is zero. As such, it equals $AnalystAsk\_D_{it} \times AnalystNum_{it}$.

suggests that the association between *AnalystAsk* and innovation should be stronger when a firm has higher agency costs. Prior studies find that CEO–chairman duality and the tunneling activities of controlling shareholders are associated with greater agency problems because of excessive CEO power and greater tunneling opportunities (Fan and Wong 2005; Jiang, Lee, and Yue 2010; Larcker, Ormazabal, and Taylor 2011). As such, we construct two variables to capture the level of agency costs in a firm. The first variable, $Duality_{it}$, is an indicator variable that equals one if the CEO is also the chairman of the board, and zero otherwise. The second variable, $Tunneling_{it}$, is an indicator variable that equals one if other receivables of the firm exceed the industry median, and zero otherwise (Jiang, Lee and Yue 2010). We add the interaction terms of *AnalystAsk_D* with $Duality_{it}$ and $Tunneling_{it}$ to the regression model and expect a positive coefficient on the interaction term if analysts' questions help monitor managers who are likely to underinvest in innovation due to agency problems.

Table 6 presents the results from this analysis. We first discuss the results using $Duality_{it}$ in Panel A. Consistent with the monitoring role of analysts in the change in R&D expenditures, the coefficient on $AnalystAsk\_D_{it} \times Duality_{it}$ is positive and significant at the 5% level. In Panel B, where we interact $AnalystAsk\_D_{it}$ with $Tunneling_{it}$, we find a positive coefficient on the interaction term, significant at the 5% level, for the analysis of the change in R&D expenditures. We do not find significant results for the analysis of the change in patent applications.

[Insert Table 6]

Overall, the results from these tests are consistent with the monitoring hypothesis and suggest that analysts' questions can help alleviate the underinvestment problem arising from agency costs.

5.3 Knowledge spillover hypothesis

Sell-side analysts specialize by industry and their within-industry expertise reflects their knowledge about the factors that affect a firm's performance relative to other firms in the industry (Kadan, Madureira, Wang, and Zach 2012). Managers are more likely to benefit from analysts' knowledge about competitors' innovation activities if they have similar technology as the focal firm (Byun, Oh, and Xia 2021). Consistent with information flows from analysts to managers, Martens and Sextroh (2021) find that a firm is more likely to cite another firm's patents if both firms are covered by the same analyst. Thus, it follows that the effect of analysts' innovation-related questions on corporate innovation should be stronger when analysts cover more firms in the same industry and thus have more information about innovation activities in other firms. Similarly, the effect of analysts' innovation-related questions on corporate innovation should be stronger when the patents of the focal firm and those of peer firms are more closely related, such that the focal firm is more likely to learn from other firms' innovation activities. To test these predictions, we construct two indicator variables: $IndCoverage_{it}$ and $TechSimilarity_{it}$. $IndCoverage_{it}$ is an indicator variable that equals one if the average number of firms in the same industry followed by an analyst who conducts site visits is above the sample median, and zero otherwise. $TechSimilarity_{it}$ is an indicator variable that equals one if the focal firm's technological similarity with industry peers is above the sample median, and zero otherwise.[12] Then, we interact $AnalystAsk\_D_{it}$ with these two variables and add them to the regression model. We expect a positive coefficient on the interaction terms if analysts' questions help diffuse knowledge regarding firms' innovation activities.

Table 7 presents the results of this analysis. We first discuss the results using $IndCoverage_{it}$ in Panel A. Consistent with analysts facilitating knowledge spillovers, the coefficient on

[12] See Appendix B for details on the construction of this variable.

AnalystAsk_D$_{it}$ × *IndCoverage*$_{it}$ is positive and significant at the 5% level in the analysis of the change in R&D.

[Insert Table 7]

In Panel B, where we interact *AnalystAsk_D*$_{it}$ with *TechSimilarity*$_{it}$, we find a significantly positive coefficient on the interaction term. Specifically, the coefficient on *AnalystAsk_D*$_{it}$ × *TechSimilarity*$_{it}$ is positive and significant at the 10% level for the analysis of the change in R&D and at the 5% level for the change in patent applications.

Overall, the results from these tests suggest that analysts' innovation-related questions have a positive impact on corporate innovation through a knowledge spillover effect.

5.4 Pressure hypothesis

Although the main results indicate a positive average effect of analysts' questions on corporate innovation, we examine whether the association is weakened when managers face greater pressure to meet capital market expectations and boost short-term earnings at the expense of long-term investments in corporate innovation. For this purpose, we construct two indicator variables, *CEOAge*$_{it}$ and *Distress*$_{it}$. *CEOAge*$_{it}$ is an indicator variable that equals one if the CEO is 55 years old or above, and zero otherwise. Prior studies find that CEOs have stronger incentives to reduce R&D expenditures in their final years of service to boost short-term earnings performance (Dechow and Sloan 1991; Barker and Mueller 2002). We use 55 years as a cutoff because 60 years is the mandatory retirement age in China.[13] *Distress*$_{it}$ is an indicator variable that equals one if the firm has received special treatment (ST) or particular transfer (PT) status in the previous two years, and zero otherwise. In China, a firm is designated as ST by the Chinese Securities Regulatory Commission if it reports a loss in two consecutive years. An ST firm is

[13] The retirement age is 60 years for men and 55 years for women. However, because CEOs are likely to retire later than the official retirement age, we use 60 years as the retirement age in the analyses.

further demoted to PT status and risks being delisted if it reports a loss in three consecutive years. The literature suggests that firms with ST or PT status are under greater pressure to increase short-term earnings (Chen, Lee, and Li 2008). Next, we interact $AnalystAsk\_D_{it}$ with these two variables and add them to the regression model. The pressure hypothesis implies a negative coefficient on the interaction terms.

Table 8 reports the results of this analysis. We first discuss the results based on $CEOAge_{it}$, as reported in Panel A. Consistent with the pressure hypothesis, we find that the coefficient on $AnalystAsk\_D_{it} \times CEOAge_{it}$ is negative and significant at the 1% and 10% levels for the analyses of the changes in R&D and patent applications, respectively. In Panel B, where we interact $AnalystAsk\_D_{it}$ with $Distress_{it}$, we find a significantly negative coefficient on the interaction term for the analysis of the change in R&D.

[Insert Table 8]

Overall, the results of this analysis suggest that the positive effect of analysts' innovation-related questions on corporate innovation is weakened when managers are under greater pressure to meet capital market expectations, consistent with the pressure effect documented in He and Tian (2013).

6. Additional analyses

6.1 Endogeneity

Whether analysts conduct site visits and ask questions about corporate innovation during site visits can be endogenous. In particular, it is likely that a change in a firm's innovation activities would induce analysts to ask questions about corporate innovation. We address this reverse causality issue in the main analyses by using lagged $AnalystAsk_{it}$ to explain future R&D

expenditures and patent applications. Below, we conduct two tests to further address potential reverse causality.

6.1.1 Lead–lag analysis

Although we focus on the change in R&D and patent applications in year t+1 to examine the causal effect of analysts' questions during site visits in year t, endogeneity can remain a concern if *AnalystAsk* is sticky over time. To mitigate potential reverse causality, we conduct a lead–lag analysis by controlling for analysts' questions in year t-1 ($AnalystAsk_{t-1}$) and year t+1 ($AnalystAsk_{t+1}$). As such, we restrict this analysis to a subsample of firms with at least one site visit per year from year t-1 to year t+1 from 2014 to 2018.

Table 9 presents the results of this analysis. We first discuss the results of the analysis of the change in R&D expenditures, as reported in columns (1) and (2). Consistent with the results reported above, we continue to find a significantly positive coefficient on $AnalystAsk_{it}$, our variable of interest measured in year t. For example, the coefficient on $AnalystAsk\_D_t$ is 0.227, implying a relative increase of 3.9% (= 0.227/5.75) of the standard deviation of $\Delta R\&D_{t+1}$ (which is 5.75 for the restricted sample). Conversely, the coefficient on $AnalystAsk_{t-1}$ is only significant in Column (2) when $AnalystAsk\_R_{t-1}$ is used.[14] In addition, we find a significantly positive coefficient on $AnalystAsk_{t+1}$ in columns (1) and (2), suggesting a contemporaneous association between analysts' questions and R&D activities.

[Insert Table 9]

The results using patent applications, presented in columns (3) and (4), are similar. Consistent with the results reported above, we find a significantly positive coefficient on $AnalystAsk_t$ in both columns. Moreover, the coefficient on the indicator variable is 0.254,

[14] The weaker results for $AnalystAsk\_R_{t-1}$ are not surprising because the time lag between $AnalystAsk_{t-1}$ and the change in R&D in year t+1 is effectively two years.

implying a relative increase of 8.7% (= 0.254/2.92) of the standard deviation of $Ln\Delta Patent_{t+1}$ (which is 2.92 for the restricted sample). We also find a contemporaneous relation between analysts' questions and patent activities, but no relation between analysts' questions in year *t*-1 and future patent applications.

Overall, our inferences remain the same after controlling for the lead–lag relation between analysts' questions during site visits and future innovations.

6.1.2 Subsample analysis

Next, we address the potential concern that our results are driven by persistent patterns in innovation activities by estimating Equation (1) on a subsample of firms that have no R&D expenditures or patent applications in the prior year. Table 10 presents the results of this analysis. In Panel A, where we examine the effect of analysts' questions on the change in R&D in year *t*+1 for firms with no R&D expenditures in year *t*-1, we continue to find a significantly positive coefficient on both *AnalystAsk* variables.[15] In Column (1), the coefficient of 0.612 implies a relative increase of 16.28% (= 0.612/3.76) of the standard deviation of $\Delta R\&D_{t+1}$ (which is 3.76 for the restricted sample). Panel B presents the results using a subsample of firms without patent applications in the prior year. We continue to find a significantly positive coefficient on both *AnalystAsk* variables. In Column (1), the coefficient of 0.295 implies a relative increase of 19.67% (= 0.295/1.50) of the standard deviation of $Ln\Delta Patent_{t+1}$ (which is 1.50 for the restricted sample).

[Insert Table 10]

Overall, our inferences remain the same after controlling for potential endogeneity.

[15] Since 2007, firms have been required to disclose R&D expenditures under China Accounting Standards. Therefore, we assume that a firm does not have any R&D expenditures in year *t*-1 if it reports zero R&D or has missing data for R&D.

Nevertheless, we admit that we cannot fully rule out the possibility that the documented results are affected by endogeneity.

6.2 The incremental effect of analysts' participation in site visits over other participants

In this section, we use the following regression model to examine the incremental effect of having analysts' participation in site visits during which the firms are asked about corporate innovation:

$$\begin{aligned} \Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} &= \beta_0 + \beta_1 AnalystAsk_{it} \times Ask\_D_{it} + \beta_2 Ask\_D_{it} + \gamma Controls_{it} + YEAR_t \\ &+ INDUSTRY_j + \varepsilon_{it+1} \end{aligned} \quad (2)$$

Ask_D_{it} is an indicator variable that equals one for firm-years with site visits in which visitors ask questions related to innovation, regardless of analyst participation, and zero otherwise. By definition, $AnalystAsk_{it}$ is zero when Ask_D_{it} is zero; that is, firm-years with positive $AnalystAsk_{it}$ is a subset of the firm-years with Ask_D_{it} being one. As such, the coefficient on Ask_D_{it} captures the effect of site visits with questions on corporate innovation without participation by financial analysts, and the coefficient on $AnalystAsk_{it} \times Ask\_D_{it}$ captures the incremental effect of analysts' participation in site visits with innovation-related questions (i.e., incremental to other participants in site visits with questions on corporate innovation).

Panel A of Table 11 reports the results of estimating Equation (2) with $\Delta R\&D_{it+1}$ as the dependent variable. In Column (1), we find that the coefficient on $AnalystAsk\_D_{it} \times Ask\_D_{it}$ is significantly positive at the 5% level, indicating that participation by analysts in site visits with innovation-related questions has an incremental effect on increases in R&D expenditures in the following year.[16] The results using the ratio variable in Column (2) are similar, where the coefficient on $AnalystAsk\_R_{it} \times Ask\_D_{it}$ is positive and significant at the 1% level.

[16] The net effect of $AnalystAsk\_D_{it}$, i.e., the sum of the coefficients on $AnalystAsk\_D_{it} \times Ask\_D_{it}$ and Ask_D_{it}, is 0.396 and significant at the 1% level.

[Insert Table 11]

Panel B of Table 11 reports the results of the analysis of the change in patent applications. In Column (1), we find that the coefficient on $AnalystAsk\_D_{it} \times Ask\_D_{it}$ is significantly positive at the 10% level, consistent with participation by analysts in site visits with innovation-related questions having an incremental effect on the increase in patent applications in the following year compared with other participants.

Overall, the results of these analyses suggest that analysts' innovation-related questions have a positive impact on corporate innovation.

7. Conclusion

Although prior studies examine the relation between analyst coverage and innovation and report mixed evidence, there is little research on the mechanism through which analysts affect corporate innovation. In this paper, we examine whether and how analysts' questions about innovation during site visits affect corporate innovation activities and outcomes. Using a sample of site visits in China, we find that when analysts ask more questions about innovation during site visits, firms invest more in R&D and file more patents in the following year. We propose four nonexclusive reasons why analysts affect corporate innovation and find evidence consistent with all four channels. Specifically, the positive association is stronger when analysts have a greater information and monitoring role. In addition, analysts' questions have a greater effect when knowledge spillovers from analysts to managers are more likely. Finally, we show that the effect of analysts' questions is weakened when managers feel pressure to meet earnings expectations.

This paper contributes to the literature by examining the mechanism through which analysts affect corporate innovation. Our findings suggest that analysts play a direct role in shaping corporate innovation through their questions about firms' innovation activities.

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APPENDIX A
Examples of Analysts' Questions about Corporate Innovation during Site Visits

1. Example related to the information hypothesis
Firm: 300119 Ringpu Ltd.
Visit date: 9/22/2016
Visit content:
The development of the H5N2 subtype (strains D7 and rD8) inactivated influenza vaccine that had already reached the review and testing phase. This vaccine is the first effective H5 subtype inactivated influenza vaccine in China. Once this vaccine reaches the production stage, it would help prevent influenza infection in poultry and birds.

Brokerage: Essence Securities
Report date: 10/14/2016
Analyst report:
The company's H5N2 subtype (strains D7 and rD8) inactivated influenza vaccine has obtained testing approval from the Ministry of Agriculture. This vaccine has broad applications and can be used for all poultry and birds. It is expected to be authorized to enter the production phase and will play a critical role in the development of the company next year. … The company's revenue is expected to increase dramatically once the H5 subtype vaccine is approved for production.

2. Example related to the monitoring hypothesis
Firm: 002422 Kelun Pharmaceutical
Visit date: 6/8/2015
Visit content:
Question: The few companies mentioned above have R&D capabilities that are similar to your company's. They have many drugs with major patents. What is the situation with your company?
Question: You mentioned earlier that the company's R&D capability is in the top tier in China. However, does the company have similar R&D capability or is the company still lagging behind the best companies?
Question: I think the company has similar R&D capability in the development of chemical medicines, genetic drugs, and innovative drugs as Hengrui Medicine, Shijiazhuang Pharma Group, and Chia Tai-Tianqing Pharmaceutical Holdings. In terms of the development of biopharmaceutical drugs, did you refer to human capital and brand names when you commented that the company has late-mover advantages?
Question: In terms of the direction of R&D, in which areas do you think the market is relatively large? … In the area of biopharmaceutical drugs, is the company lagging behind Hengrui Medicine and Qilu Pharmaceutical?

3. Example related to the knowledge spillover hypothesis
Firm: 300570 T&S Communications（太辰光）
Visit date: 12/28/2016
Visit content:

Question: The telecommunications equipment industry has a very fast product turnover. In terms of optical communication products, the international trend is to focus on 40G and 100G products. The key companies in the industry such as Accelink Technologies and InnoLight are developing 400G optical communication products. Could you please share the company's plan in the development of such high-end products?

Question: Are the company's ceramic ferrule products and the ceramic sleeve products from TFC Optical substitutes in applications? Has the company competed or collaborated with TFC?

4. Example related to the pressure hypothesis
Firm: 000550 Jiangling Motors Ltd.
Visit date: 11/30/2018
Visit content:
Question: The company reported its first loss in the last 10 years in this Q3. The company's R&D expenditures are way too high, with an annual R&D budget of 2 billion yuan. The R&D expenditures have reached 10.7 billion yuan since the company started to disclose R&D expenditures in 2007. How is the company going to balance the short- and long-term goals?

APPENDIX B
Variable Definitions

Variable	Definition
Dependent variables	
$\Delta R\&D_{t+1}$	The change in R&D expenditures in year t+1, calculated as $\frac{\left[R\&D_{it+1}-\frac{1}{2}(R\&D_{it-1}+R\&D_{it-2})\right]}{\frac{1}{2}(Revenue_{it-1}+Revenue_{it-2})} \times 100$, where *R&D* is R&D expenditures and *Revenue* is total sales.
$\Delta Patent_{t+1}$	The change in the number of patent applications in year t+1, calculated as $Patent\_app_{it+1} - \frac{1}{2}(Patent\_app_{t-1} + Patent\_app_{t-2})$, where *Patent_app* is the number of patent applications in a given year.
$Ln\Delta Patent_{it+1}$	The natural logarithm of the change in patent applications in year t+1, calculated as $Ln\ (\Delta Patent_{t+1} + 1)\ if\ \Delta Patent_{t+1} \geq 0$, and $-Ln(-\Delta Patent_{t+1} + 1)\ if\ \Delta Patent_{t+1} < 0$.
Independent variables	
$AnalystAsk\_D_{it}$	Indicator variable for analysts asking questions about innovation, equals one if there is at least one site visit with security analyst participants in which firm *i* is asked about innovation in year *t*, and zero otherwise. We identify questions about innovation through the following nine keywords in site visits' transcripts: "technology," "R&D," "science and technology," "development," "innovation," "laboratory," "research," "patent," and "invention."
$AnalystAsk\_R_{it}$	Ratio variable for analysts asking questions about innovation, i.e., number of site visits with security analyst participants in which firm *i* is asked about innovation, divided by the total number of site visits to firm *i* in year *t*.
ASK_D_{it}	Indicator variable for firm-years with site visits with questions about innovation, equals one if there is at least one site visit in which firm *i* is asked about innovation in year *t*, and zero otherwise.
Control variables	
AC_{it}	Analyst following, calculated as the natural logarithm of one plus the number of analysts following firm *i* in year *t*.
$Size_{it}$	Firm size, calculated as the natural logarithm of total assets (in yuan) of firm *i* in year *t*.
Age_{it}	Firm age, calculated as the number of years between the founding of firm *i* and year *t*.
$Leverage_{it}$	Leverage, calculated as firm *i*'s total liabilities divided by total assets in year *t*.
$Profit_{it}$	Indicator variable for the firm's profit, equals one if the net profit of firm *i* in year *t* is positive, and zero otherwise.
BM_{it}	Book-market ratio of firm *i* in year *t*, calculated as the book value of equity divided by the market value of equity.
$R\&D_{it}$	Lagged R&D expenditures, calculated based on R&D expenditures in years *t*-1 and *t*-2: $\frac{R\&D_{it-1}+R\&D_{it-2}}{Revenue_{it-1}+Revenue_{it-2}} \times 100$
$CASH_{it}$	Cash of firm *i* at the end of year *t*, divided by total assets in year *t*.
PPE_{it}	Property, plant, and equipment of firm *i* in year *t*, divided by total assets in year *t*.

$CAPEX_{it}$	Capital expenditure of firm *i* in year *t*, divided by total assets in year *t*.
$InstOwn_{it}$	Percentage of institutional holdings of firm *i* in year *t*.
HHI_{it}	Herfindahl index of the industry to which firm *i* belongs in year *t*. It is calculated as the sum of the square of the ratio of a firm's sales to industry sales across all firms in the industry to which firm *i* belongs.
HHI^2_{it}	Squared HHI_{it}.
$KZindex_{it}$	Kaplan–Zingales (KZ; 1997) index of firm *i* in year *t,* calculated as follows. First, *KZ1* equals one if *cash flow/PPE* is lower than the sample median in year *t*, *KZ2* equals one if *Tobin's q* is higher than the sample median in year *t*, *KZ3* equals one if *Leverage* is higher than the sample median in year *t*, *KZ4* equals one if *Dividends/PPE* is lower than the sample median in year *t*, and *KZ5* equals one if *cash holdings/PPE* is lower than the sample median in year *t*. *KZ = KZ1+KZ2+KZ3+KZ4+KZ5*. Second, we estimate the following model by year: $KZ = \alpha_0 + \alpha_1 cash\ flow_{it}/PPE_{it-1} + \alpha_2 Tobin's\ Q_{it} + \alpha_3 Leverage_{it} + \alpha_4 Dividends_{it}/PPE_{t-1} + \alpha_5 cash\ holdings_{it}/PPE_{it-1} + \varepsilon_{it}$ Third, *KZindex* for firm *i* in year *t* is the predicted value of KZ calculated via the estimated coefficients obtained from the second step.

Cross-sectional variables

$AnalystNum_{it}$	Indicator variable for analysts participating in site visits, equals one if the average number of analyst participants in site visits where firm *i* is asked about innovation in year *t* exceeds the sample median, and zero otherwise.
$NewsCov_{it}$	Indicator variable for news coverage of the firm, equals one if the number of news reports about firm *i* in year *t* exceeds the sample median, and zero otherwise.
$Duality_{it}$	Indicator variable for CEO–chairman duality, equals one if the CEO of firm *i* in year *t* is also the chairman of the board, and zero otherwise.
$Tunneling_{it}$	Indicator variable for tunneling, measured by other receivables divided by revenue. It is set to one if other receivables divided by the revenue of firm *i* in year *t* exceed the sample median, and zero otherwise.
$IndCoverage_{it}$	Indicator variable for analysts' industry coverage, equals one if the average number of firms in the same industry followed by each brokerage that conducts site visits to firm *i* in year *t* exceeds the sample median, and zero otherwise.
$TechSimilarity_{it}$	Indicator variable for technology spillovers, equals one if the technological similarity ($Tech\_spillover$) of firm *i* to industry peers in year *t* exceeds the sample median, and zero otherwise. Following Byun, Oh, and Xia (2021), we first calculate the correlation between firm *i* and firm *j*'s patent composition as below. $$Techcorr_{ij,t} = \frac{\boldsymbol{X}_{i,t}\boldsymbol{X}'_{j,t}}{(\boldsymbol{X}_{i,t}\boldsymbol{X}'_{i,t})^{0.5}(\boldsymbol{X}_{j,t}\boldsymbol{X}'_{j,t})^{0.5}}$$ where $\boldsymbol{X}_{i,t} = (X_{i1,t}, X_{i2,t}, X_{i3,t})$ is a vector denoting the proportion of patents in the three types: invention patents, new practical patents, and appearance design patents, of firm *i* in year *t*. $\boldsymbol{X}_{j,t}$ is defined similarly. We calculate technological spillover potential for firm *i* with industry peers in year *t* based on the weighted average of *Techcorr*:

	$$Tech\_spillover_{i,t} = \sum_{j=1}^{J} Techcorr_{ij,t} \times RD_{j,t}$$ where $RD_{j,t}$ is firm *j*'s R&D expenditures divided by revenue in year *t*. *J* is the number of firms in the industry to which firm *i* belongs. A higher value of $Tech\_spillover$ indicates a larger technological spillover possibility of firm *i* with its industry peers.
$CEOAge_{it}$	Indicator variable equal to one if the CEO of firm *i* in year *t* is aged 55 years and above, and zero otherwise.
$Distress_{it}$	Indicator variable for firms' distress risk, equals one if firm *i* received Special Treatment (ST) or Particular Transfer (PT) status in year *t-1* or *t-2*, and zero otherwise.

TABLE 1
Sample Selection

This table presents the sample selection process. The final sample includes 7,284 firm-years during the 2013–2019 period.

	No. of site visits	No. of firm-years	No. of unique firms
Site visits during 2013–2019	47,310	9,172	2,331
After excluding firm-years with missing values for the variables used in the regression analyses	42,458	7,525	1,888
After excluding firm-years with missing information on visitor identities	41,257	7,284	1,851

TABLE 2
Descriptive Statistics

This table presents descriptive statistics for the key variables. Panel A reports summary statistics and Panel B reports the correlation matrix. The sample includes 7,284 firm-years for 2013–2019. For Panel B, * indicates significance at the 1% level. Spearman (Pearson) correlation coefficients are presented in the upper (lower) triangle. See Appendix B for variable definitions.

Panel A: Descriptive statistics

	N	Mean	Std.	Q1	Median	Q3
Dependent variables						
$\Delta R\&D_{t+1}$	7,284	3.103	5.642	0.022	1.393	4.087
$\Delta Patent_{t+1}$	7,284	13.938	78.595	–5.000	2.000	19.500
$Ln\Delta Patent_{t+1}$	7,284	0.654	2.830	–1.792	1.099	3.020
Independent variables of interest						
$AnalystAsk\_D_{it}$	7,284	0.563	0.496	0.000	1.000	1.000
$AnalystAsk\_R_{it}$	7,284	0.282	0.337	0.000	0.154	0.500
Control variables						
AC_{it} *(Raw value)*	7,284	6.637	6.623	2.000	5.000	10.000
$Size_{it}$ *(CNY in billions)*	7,284	9.452	37.042	1.704	3.322	7.116
Age_{it}	7,284	7.955	6.235	3.000	6.000	10.000
$Leverage_{it}$	7,284	0.387	0.195	0.227	0.374	0.530
$Profit_{it}$	7,284	0.934	0.249	1.000	1.000	1.000
BM_{it}	7,284	0.350	0.226	0.189	0.294	0.446
$R\&D_{it}$ *(%)*	7,284	4.501	4.482	1.676	3.577	5.555
$CASH_{it}$	7,284	0.162	0.121	0.075	0.127	0.211
PPE_{it}	7,284	0.198	0.144	0.087	0.170	0.278
$CAPEX_{it}$	7,284	0.052	0.046	0.018	0.038	0.071
$InstOwn_{it}$ *(%)*	7,284	38.558	24.734	15.140	38.970	59.430
HHI_{it}	7,284	0.087	0.101	0.028	0.060	0.109
HHI^2_{it}	7,284	0.018	0.067	0.001	0.004	0.012
$KZindex_{it}$	7,284	1.312	2.048	0.104	1.477	2.689

TABLE 2 (cont'd)

Panel B: The correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$\Delta R\&D_{t+1}$ (1)		0.273*	0.224*	0.235*	0.226*	–0.131*	–0.242*	–0.187*	0.152*	–0.262*	0.474*	0.173*	–0.139*	0.126*	–0.142*	–0.257*	–0.257*	–0.191*
$Ln\Delta Patent_{t+1}$ (2)	0.215*		0.110*	0.087*	0.174*	0.102*	–0.056*	0.053*	0.082*	–0.074*	0.087*	0.021	–0.004	0.081*	0.013	–0.026	–0.026	–0.006
AnalystAsk_D (3)	0.161*	0.085*		0.894*	0.155*	–0.085*	–0.152*	–0.094*	0.051*	–0.133*	0.252*	0.107*	–0.066*	0.073*	–0.075*	–0.109*	–0.109*	–0.087*
AnalystAsk _R (4)	0.170*	0.030	0.739*		0.075*	–0.123*	–0.161*	–0.115*	0.045*	–0.153*	0.276*	0.107*	–0.076*	0.070*	–0.094*	–0.145*	–0.145*	–0.079*
AC (5)	0.166*	0.127*	0.175*	0.033*		0.305*	–0.035*	0.002	0.190*	–0.120*	0.065*	0.087*	–0.075*	0.119*	0.153*	0.033*	0.008	–0.112*
Size (6)	–0.097*	–0.004	–0.076*	–0.124*	0.298*		0.516*	0.560*	0.019	0.442*	–0.356*	–0.256*	–0.022	–0.091*	0.364*	0.132*	0.132*	0.293*
Age (7)	–0.177*	–0.088*	–0.154*	–0.141*	–0.009	0.545*		0.359*	–0.076*	0.278*	–0.324*	–0.198*	0.074*	–0.208*	0.288*	0.091*	0.091*	0.255*
Leverage (8)	–0.148*	–0.005	–0.100*	–0.111*	0.018	0.563*	0.356*		–0.140*	0.154*	–0.382*	–0.393*	0.032	–0.060*	0.233*	0.167*	0.167*	0.718*
Profit (9)	0.091*	0.095*	0.056*	0.034*	0.177*	0.016	–0.055*	–0.162*		0.015	0.037*	0.102*	–0.088*	0.030	0.025	–0.017	–0.017	–0.222*
BM (10)	–0.203*	–0.196*	–0.148*	–0.133*	–0.101*	0.499*	0.352*	0.204*	–0.007		–0.276*	–0.180*	0.180*	–0.019	0.124*	0.141*	0.141*	–0.035*
R&D (11)	0.415*	–0.012	0.213*	0.234*	0.065*	–0.282*	–0.272*	–0.336*	0.001	–0.235*		0.246*	–0.143*	0.073*	–0.287*	–0.384*	–0.384*	–0.234*
CASH (12)	0.145*	0.049*	0.094*	0.083*	0.108*	–0.253*	–0.159*	–0.398*	0.098*	–0.196*	0.264*		–0.295*	–0.044*	–0.037*	–0.119*	–0.119*	–0.586*
PPE (13)	–0.177*	–0.002	–0.078*	–0.086*	–0.105*	0.048*	0.107*	0.058*	–0.069*	0.169*	–0.220*	–0.288*		0.442*	0.112*	0.071*	0.071*	–0.008
CAPEX (14)	0.047*	0.044*	0.066*	0.042*	0.107*	–0.054*	–0.177*	–0.038*	0.034*	–0.051*	0.005	–0.075*	0.332*		0.008	–0.015	–0.015	–0.115*
InstOwn (15)	–0.098*	0.017	–0.063*	–0.083*	0.144*	0.378*	0.329*	0.220*	0.045*	0.130*	–0.243*	–0.044*	0.152*	0.017		0.159*	0.159*	0.068*
HHI (16)	–0.114*	–0.006	–0.074*	–0.090*	0.025	0.074*	0.074*	0.079*	–0.022	0.032*	–0.205*	–0.037*	0.078*	0.052*	0.114*		1.000*	0.099*
HHI^2 (17)	–0.052*	–0.008	–0.031*	–0.036*	0.025	0.027	0.044*	0.032*	–0.022	–0.001	–0.092*	0.003	0.047*	0.056*	0.055*	0.883*		0.099*
KZindex (18)	–0.152*	–0.003	–0.079*	–0.061*	–0.120*	0.275*	0.219*	0.682*	–0.222*	0.029	–0.187*	–0.629*	0.028	–0.083*	0.054*	0.036*	0.011	

TABLE 3
Analysts' Questions about Innovation and Future R&D Investments

This table presents the regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments:

$$\begin{aligned}\Delta R\&D_{it+1} = {} & \beta_0 + \beta_1 AnalystAsk_{it} + \gamma_1 AC_{it} + \gamma_2 Size_{it} + \gamma_3 Age_{it} + \gamma_4 Leverage_{it} + \gamma_5 Profit_{it} + \gamma_6 BM_{it} \\ & + \gamma_7 R\&D_{it} + \gamma_8 CASH_{it} + \gamma_9 PPE_{it} + \gamma_{10} CAPEX_{it} + \gamma_{11} InstOwn_{it} + \gamma_{12} HHI_{it} + \gamma_{13} HHI_{it}^2 \\ & + \gamma_{14} KZindex_{it} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}\end{aligned}$$

$AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Dependent variable =	$\Delta R\&D_{t+1}$	
AnalystAsk =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$	**0.409*** **	**0.968*** **
	(3.22)	**(4.49)**
AC_{it}	0.504***	0.529***
	(5.68)	(5.98)
$Size_{it}$	0.208*	0.219*
	(1.74)	(1.85)
Age_{it}	–0.019	–0.018
	(–1.20)	(–1.14)
$Leverage_{it}$	3.068***	3.080***
	(4.16)	(4.19)
$Profit_{it}$	1.047***	1.026***
	(3.90)	(3.83)
BM_{it}	–2.610***	–2.595***
	(–6.05)	(–6.02)
$R\&D_{it}$	0.412***	0.406***
	(9.67)	(9.60)
$CASH_{it}$	–4.658***	–4.719***
	(–4.52)	(–4.59)
PPE_{it}	–3.602***	–3.554***
	(–6.16)	(–6.10)
$CAPEX_{it}$	4.499**	4.354**
	(2.34)	(2.27)
$InstOwn_{it}$	–0.041	–0.062
	(–0.12)	(–0.18)
HHI_{it}	–3.255*	–3.022*
	(–1.79)	(–1.66)
HHI^2_{it}	2.659	2.386
	(1.33)	(1.19)
$KZindex_{it}$	–0.558***	–0.563***
	(–6.65)	(–6.74)
Year fixed effects	YES	YES

Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.287	0.289

TABLE 4
Analysts' Questions about Innovation and Future Patent Applications

This table presents the regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future patent applications:

$$Ln\Delta Patent_{it+1} = \beta_0 + \beta_1 AnalystAsk_{it} + \gamma_1 AC_{it} + \gamma_2 Size_{it} + \gamma_3 Age_{it} + \gamma_4 Leverage_{it} + \gamma_5 Profit_{it} + \gamma_6 BM_{it} + \gamma_7 R\&D_{it} + \gamma_8 CASH_{it} + \gamma_9 PPE_{it} + \gamma_{10} CAPEX_{it} + \gamma_{11} InstOwn_{it} + \gamma_{12} HHI_{it} + \gamma_{13} HHI_{it}^2 + \gamma_{14} KZindex_{it} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}$$

$AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Dependent variable =	$Ln\Delta Patent_{t+1}$	
AnalystAsk =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$	**0.234*** **	**0.213** **
	(3.57)	**(2.33)**
AC_{it}	0.139***	0.156***
	(3.32)	(3.73)
$Size_{it}$	0.158***	0.160***
	(2.70)	(2.72)
Age_{it}	–0.020***	–0.020***
	(–3.01)	(–3.09)
$Leverage_{it}$	1.094***	1.104***
	(3.71)	(3.73)
$Profit_{it}$	0.557***	0.557***
	(4.48)	(4.49)
BM_{it}	–0.722***	–0.734***
	(–2.92)	(–2.96)
$R\&D_{it}$	–0.015	–0.014
	(–1.53)	(–1.43)
$CASH_{it}$	–0.553	–0.559
	(–1.38)	(–1.40)
PPE_{it}	–0.482	–0.488
	(–1.62)	(–1.63)
$CAPEX_{it}$	2.177***	2.214***
	(2.83)	(2.88)
$InstOwn_{it}$	0.010	0.002
	(0.07)	(0.01)
HHI_{it}	–1.141	–1.153
	(–1.50)	(–1.51)
HHI^2_{it}	0.628	0.646
	(0.58)	(0.59)
$KZindex_{it}$	–0.135***	–0.137***
	(–4.77)	(–4.81)
Year fixed effects	YES	YES

Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.244	0.243

TABLE 5
Analysts' Questions about Innovation and Future R&D Expenditures and Patent Applications: Tests of the Information Hypothesis

This table presents the regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments and patent applications conditional on proxies for analysts' information role:

$$\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} = \beta_0 + \beta_1 AnalystAsk\_D_{it} \times AnalystNum_{it}(NewsCov_{it}) + \beta_2 AnalystAsk\_D_{it} + \beta_3(NewsCov_{it}) + \boldsymbol{\gamma Controls_{it}} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}$$

The proxies for analysts' information role are the number of analysts participating in site visits during which questions about corporation innovation are asked ($AnalystNum_{it}$) and media coverage of the firm ($NewsCov_{it}$). The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Panel A: Number of analysts participating in site visits (AnalystNum)

Dependent variable =	$\Delta R\&D_{t+1}$	$Ln\Delta Patent_{t+1}$
	(1)	(2)
$AnalystAsk\_D_{it} \times AnalystNum_{it}$	**0.949*** **	**0.039**
	(5.28)	**(0.46)**
$AnalystAsk\_D_{it}$	–0.014	0.217***
	(–0.10)	(2.82)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.291	0.244

Panel B: Media coverage (NewsCov)

Dependent variable =	$\Delta R\&D_{t+1}$	$Ln\Delta Patent_{t+1}$
	(1)	(2)
$AnalystAsk\_D_{it} \times NewsCov_{it}$	**0.928*** **	**0.459*** **
	(3.84)	**(3.86)**
$AnalystAsk\_D_{it}$	–0.039	0.013
	(–0.25)	(0.15)
$NewsCov_{it}$	0.211	–0.122
	(1.05)	(–1.24)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,283	7,283
Adj. R^2	0.292	0.246

TABLE 6
Analysts' Questions about Innovation and Future R&D Expenditures and Patent Applications: Tests of the Monitoring Hypothesis

This table presents the regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments and patent applications conditional on proxies for firms' agency problems:

$$\begin{aligned}\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} &= \beta_0 + \beta_1 AnalystAsk\_D_{it} \times Duality_{it}(Tunneling_{it}) + \beta_2 AnalystAsk\_D_{it} \\ &+ \beta_3 Duality_{it}(Tunneling_{it}) + \boldsymbol{\gamma Controls_{it}} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}\end{aligned}$$

The proxies for firms' agency problems are an indicator for CEO–chairman duality ($Duality_{it}$) and tunneling by controlling shareholders, measured by other receivables divided by sales ($Tunneling_{it}$). The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Panel A: CEO–chairman duality (Duality)

Dependent variable =	$\Delta R\&D_{t+1}$	$Ln\Delta Patent_{t+1}$
	(1)	(2)
AnalystAsk_D$_{it}$* × *Duality$_{it}$	**0.388****	**0.010**
	(2.05)	**(0.08)**
AnalystAsk_D$_{it}$	0.234**	0.220***
	(2.36)	(2.78)
Duality$_{it}$	–0.053	0.091
	(–0.36)	(0.88)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.352	0.243

Panel B: Tunneling by controlling shareholders (Tunneling)

Dependent variable =	$\Delta R\&D_{t+1}$	$Ln\Delta Patent_{t+1}$
	(1)	(2)
AnalystAsk_D$_{it}$* × *Tunneling$_{it}$	**0.554****	**–0.018**
	(2.31)	**(–0.15)**
AnalystAsk_D$_{it}$	0.144	0.245***
	(1.00)	(2.69)
Tunneling$_{it}$	0.189	0.090
	(1.04)	(0.96)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,281	7,281
Adj. R^2	0.289	0.245

TABLE 7
Analysts' Questions about Innovation and Future R&D Expenditures and Patent Applications: Tests of the Knowledge Spillover Hypothesis

This table presents the regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments and patent applications conditional on the potential for knowledge spillovers across firms:

$$\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1}$$
$$= \beta_0 + \beta_1 AnalystAsk\_D_{it} \times IndCoverage_{it}(TechSimilarity_{it}) + \beta_2 AnalystAsk\_D_{it}$$
$$+ \beta_3 IndCoverage_{it}(TechSimilarity_{it}) + \boldsymbol{\gamma Controls_{it}} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}$$

The proxies for potential spillover effects are the number of firms in the same industry covered by visiting analysts ($IndCoverage_{it}$) and the technological similarity between the focal firm and other firms in the industry ($TechSimilarity_{it}$). The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Panel A: Number of firms in the same industry covered by visiting analysts (IndCoverage)

Dependent variable =	*ΔR&D$_{t+1}$*	*LnΔPatent$_{t+1}$*
	(1)	(2)
AnalystAsk_D$_{it}$* × *IndCoverage$_{it}$	**0.468****	**0.064**
	(2.04)	**(0.51)**
AnalystAsk_D$_{it}$	0.192	0.191**
	(1.07)	(2.31)
IndCoverage$_{it}$	–0.788***	0.101
	(–3.82)	(0.94)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.290	0.245

Panel B: Firms' technological similarity to industry peers (TechSimilarity)

Dependent variable =	*ΔR&D$_{t+1}$*	*LnΔPatent$_{t+1}$*
	(1)	(2)
AnalystAsk_D$_{it}$* × *TechSimilarity$_{it}$	**0.314***	**0.283****
	(1.85)	**(2.22)**
AnalystAsk_D$_{it}$	0.262**	0.078
	(2.54)	(0.93)
TechSimilarity$_{it}$	0.201	0.222**
	(1.34)	(2.01)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,274	7,274
Adj. R^2	0.342	0.248

TABLE 8
Analysts' Questions about Innovation and Future R&D Expenditures and Patent Applications: Tests of the Pressure Hypothesis

This table presents the regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments and patent applications conditional on firms' pressure to increase short-term earnings:

$$\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} = \beta_0 + \beta_1 AnalystAsk\_D_{it} \times CEOAge_{it}(Distress_{it}) + \beta_2 AnalystAsk\_D_{it} + \beta_3 CEOAge_{it}(Distress_{it}) + \boldsymbol{\gamma Controls_{it}} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}$$

The proxies for firms' pressure to increase short-term earnings are CEO age ($CEOAge_{it}$) and distress risk ($Distress_{it}$). The t-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Panel A: CEO age (CEOAge)

Dependent variable =	$\Delta R\&D_{t+1}$	$Ln\Delta Patent_{t+1}$
	(1)	(2)
$\boldsymbol{AnalystAsk\_D_{it} \times CEOAge_{it}}$	**–0.878***	**–0.270***
	(–2.97)	**(–1.71)**
$AnalystAsk\_D_{it}$	0.575***	0.279***
	(4.04)	(4.04)
$CEOAge_{it}$	0.438**	–0.001
	(2.09)	(–0.01)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,275	7,275
Adj. R^2	0.288	0.242

Panel B: Firms' distress risk (Distress)

Dependent variable =	$\Delta R\&D_{t+1}$	$Ln\Delta Patent_{t+1}$
	(1)	(2)
$\boldsymbol{AnalystAsk\_D_{it} \times Distress_{it}}$	**–1.906**	**–0.271**
	(–2.19)	**(–0.74)**
$AnalystAsk\_D_{it}$	0.461***	0.241***
	(3.57)	(3.62)
$Distress_{it}$	1.846***	0.155
	(2.91)	(0.73)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.289	0.244

TABLE 9
Lead–lag Analysis of Analysts' Questions about Innovation and Future Patent Applications

This table presents the lead–lag regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments and patent applications using a sample of firms that have site visits in years *t*-1, *t*, and *t*+1:

$$\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} = \beta_0 + \beta_1 AnalystAsk_{it} + \beta_2 AnalystAsk_{it-1} + \beta_3 AnalystAsk_{it+1} + \boldsymbol{\gamma Controls_{it}} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}$$

AnalystAsk is one of the following two variables: *AnalystAsk_D* and *AnalystAsk_R*. The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Dependent variable =	$\Delta R\&D_{t+1}$		$Ln\Delta Patent_{t+1}$	
AnalystAsk =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)	(3)	(4)
$AnalystAsk_t$	**0.227***	**0.656****	**0.254*****	**0.248***
	(1.73)	**(2.55)**	**(2.94)**	**(1.92)**
$AnalystAsk_{t-1}$	–0.117	0.676**	–0.057	–0.199
	(–0.89)	(2.30)	(–0.66)	(–1.38)
$AnalystAsk_{t+1}$	0.583***	0.697**	0.200**	0.201
	(4.02)	(2.53)	(2.25)	(1.53)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	4,030	4,030	4,030	4,030
Adj. R^2	0.334	0.312	0.244	0.242

TABLE 10
Subsample Analysis of Analysts' Questions about Innovation and Future R&D Expenditures and Patent Applications

This table presents the regression results for the impact of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments and patent applications using a subsample of firms that have no R&D expenditures or patent applications in the prior year:

$$\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} = \beta_0 + \beta_1 AnalystAsk_{it} + \boldsymbol{\gamma Controls_{it}} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}$$

AnalystAsk is one of the following two variables: *AnalystAsk_D* and *AnalystAsk_R*. Panel A (B) consists of firm-years with no R&D expenditures (no patent applications) in year *t*-1. The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Panel A: Analysis of the change in R&D expenditures ($\Delta R\&D_{t+1}$)

Dependent variable =	$\Delta R\&D_{t+1}$	
AnalystAsk =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$	**0.612****	**2.174****
	(2.22)	**(2.45)**
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	679	679
Adj. R^2	0.235	0.235

Panel B: Analysis of the change in patent applications ($Ln\Delta Patent_{t+1}$)

Dependent variable =	$Ln\Delta Patent_{t+1}$	
AnalystAsk =	$AnalystAsk\_D_{it}$	*AnalystAsk_Rit*
	(1)	(2)
$AnalystAsk_{it}$	**0.295*****	**0.222***
	(3.49)	**(1.69)**
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	1,233	1,233
Adj. R^2	0.143	0.137

TABLE 11
Analysts' Questions about Innovation and Future R&D Expenditures and Patent Applications: Controlling for Participation by Other Visitors

This table presents the regression results for the incremental effect of the likelihood of financial analysts asking questions about innovation during site visits on future R&D investments and patent applications:

$$\Delta R\&D_{it+1}, Ln\Delta Patent_{it+1} = \beta_0 + \beta_1 AnalystAsk_{it} \times ASK\_D_{it} + \beta_2 ASK\_D_{it} + \boldsymbol{\gamma Controls_{it}} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1}$$

$AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. Ask_D_{it} is an indicator variable equal to one for firm-years with site visits involving questions about innovation, and zero otherwise. The *t*-values in brackets are based on standard errors adjusted for firm-level clustering. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. See Appendix B for variable definitions.

Panel A: Analysis of the change in R&D expenditures ($\Delta R\&D_{t+1}$)

Dependent variable =	$\Delta R\&D_{t+1}$	
AnalystAsk =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$\boldsymbol{AnalystAsk_{it} \times ASK\_D_{it}}$	**0.541****	**1.130*****
	(2.08)	**(4.04)**
ASK_D_{it}	–0.145	–0.168
	(–0.56)	(–1.03)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.287	0.289

Panel B: Analysis of the change in patent applications ($Ln\Delta Patent_{t+1}$)

Dependent variable =	$Ln\Delta Patent_{t+1}$	
AnalystAsk =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$\boldsymbol{AnalystAsk_{it} \times ASK\_D_{it}}$	**0.263***	**0.019**
	(1.74)	**(0.15)**
ASK_D_{it}	–0.032	0.201**
	(–0.22)	(2.25)
Control variables	YES	YES
Year fixed effects	YES	YES
Industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.244	0.244