How Do Analysts Affect Corporate Innovation? Evidence from Site Visits*

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Abstract

While prior studies have examined whether financial analysts affect corporate innovation, there is little research on the mechanism through which this occurs. In this paper, we examine whether and how analysts' questions about innovation during site visits affect corporate innovation. Using a sample of corporate site visits in China, we find that when analysts ask questions about innovation during site visits, firms invest more in research and development in the future. Consistent with knowledge diffusion across firms, this association is stronger when analysts cover more firms in the same industry, firms share similar technologies as industry peers, and when an innovation-expert analyst is present at site visits. We also find that analysts' questions about innovation during site visits are positively associated with the quantity and quality of firms' patent applications in the future. Overall, we provide evidence that analysts can affect corporate innovation through their questions about firms' innovation activities.

Key words: Questions about innovation, 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 & Ross, 1990). Agency theory predicts that risk-averse managers do not undertake the optimal amount of investment in corporate innovation (Jensen & Meckling, 1976). In addition, because of information asymmetry regarding corporate innovation, capital markets might not fully incorporate the potential benefits of corporate innovation, reducing firm value and increasing the likelihood of firms being hostile takeover targets (e.g., Stein, 1988). These market frictions imply that firms are likely to underinvest in corporate innovation and instead invest 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 document that analyst coverage is associated with firms' investments in innovation (e.g., Derrien & Kecskes, 2013; He & Tian, 2013; Guo et al., 2019), but there is little research on *how* analysts shape corporate innovation. This paper contributes to this line of literature 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.

Corporate site visits refer to investors' trips to a firm's headquarters and its production facilities. They provide analysts with the opportunities to observe corporate research labs and production facilities and interact with corporate management. Prior research finds that these events are informative to capital market participants and can help analysts improve their forecast accuracy (e.g., Cheng et al., 2016; Bowen et al., 2018; Han et al., 2018; Cheng et al., 2019). While these studies hypothesize and provide evidence consistent with information flowing from managers to analysts, it's also possible for site visits to enhance the information sets of managers. Compared with managers, analysts typically cover several firms in the same industry and are thus more informed about the industry landscape and future trends. This knowledge can then be shared (consciously or subconsciously) with management during site visits, especially when analysts ask pertinent questions. Such inquiries can benefit firm managers by providing them with additional insights and enable them to make more informed decisions about the firm's innovation activities.

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 et al., 2000; Luong et al., 2017). 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 argue that analysts' questions on innovation during site visits 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. When analysts ask questions about corporate innovation during site visits, they can share the information about industry peers' innovation activities and help managers to better understand the potential benefits of investing in specific technologies. The above discussion suggests that firms with analysts asking questions about corporate innovation during site visits will experience a greater increase in innovation activities in the future. We refer to this prediction as the *knowledge spillover hypothesis*.

We test the knowledge spillover hypothesis by examining the R&D investments of firms with analysts' site visits. Using a sample of 7,284 firm-years in China from 2013 to 2019, we find that firms increase their R&D investments in the following year when they are asked about innovation activities during site visits involving analyst participation. 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 press news on innovation and firm characteristics that might affect 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 an increase in R&D expenditures by 6.7% of the sample standard deviation in the following year.

The positive association between analysts asking innovation-related questions during site visits and firms' future innovation is inconsistent with the pressure hypothesis suggested by He and Tian (2013). The pressure hypothesis implies that some of the analysts' innovation-related questions can impose pressure on firms to meet short-term earnings forecasts issued by analysts, and therefore, have a negative impact on future R&D investments.

We use analysts' questions on innovation in the current year to explain *future* innovation activities to address the potential confounding effect of the contemporaneous relation between the two constructs and the impact of potential reverse causality in the main analyses. Nevertheless, it's possible that some firm characteristics such as industry competition can motivate analysts to ask questions about innovation during site visits and firms to increase innovation investments at the same time. We conduct several analyses to address this potential endogeneity. First, we use the initial coverage of an innovation-expert analyst as a shock to the likelihood of analysts asking innovation-related questions during site visits since the innovation-expert analyst's coverage decision is unlikely to be correlated with the firm's *future* innovation activities. Yet, the innovation expert's coverage is likely to increase the likelihood of analysts' questions on corporate innovation during site visits. Like Cen et al. (2021), we consider an analyst as an innovation expert if she has had more exposure to innovation-related questions during site visits in the past. We confirm that a firm is indeed more likely to increase its R&D expenditures in the future when an innovation-expert analyst initiates coverage of the firm. Second, to address the possibility that analysts ask questions about innovation because the hosting firm presented its *future* R&D plans before the Q&A session of site visits, we restrict our sample to site visits where innovation-related keywords are mentioned in analysts' questions first. For these site visits, analysts ask questions on innovation before management presentations and are thus unlikely to be responding to R&D plans potentially shared by management during the site visits. The results from this subsample analysis remain the same. Lastly, we replace the industry fixed effects in our main specification with firm fixed effects to control for time-invariant firm characteristics. Our inferences remain the same.

After documenting a positive average effect of analysts' questions during site visits on corporate innovation, we next conduct a series of cross-sectional analyses to provide more direct evidence on the knowledge spillover hypothesis. Consistent with managers learning about industry peers' innovation activities from analysts' questions, we find that analysts' questions on innovation have a bigger effect on a firm's future R&D investments when the visiting analysts cover more firms in the same industry, when the firm exhibits a greater degree of technological similarities with other firms in the same industry, and when the firm is covered by more innovation-expert analysts, the cases where knowledge spillover is more likely to occur.

One might argue that the results documented in this paper are driven by analysts' informational or monitoring role. 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 firms with high innovation investments, leading managers to invest more in R&D. To the extent that the positive association we document is attributable to analysts' information role, the effect should be stronger for firms with a poor information environment. Using several commonly-used proxies for firms' information environment quality – analyst coverage, firm size, and media coverage, we find that the positive association between analysts' questions on innovation and future investments in R&D is *weaker* for firms with a poor information environment, suggesting that our results are unlikely to be explained by analysts' information role.

Likewise, analysts' questions can also positively affect innovation through a corporate governance mechanism (Jensen & Meckling, 1976; Healy & Palepu, 2001). When analysts interact with management, they can directly question whether management is investing sufficiently in R&D to enhance existing or to develop new technologies. Therefore, their questions may exert pressure on managers who otherwise might underinvest in innovation. To the extent that the positive association we document is attributable to analysts' monitoring role, the effect should be stronger for firms with weaker corporate governance. Using several commonly-used proxies for the extent of agency costs in Chinese firms – large shareholders' ownership and board effort, we find that the positive association between analysts' questions on innovation and future investments in R&D is *not stronger* for firms with greater agency costs, suggesting that our results are unlikely to be explained by analysts' monitoring role.

We conduct two additional tests to ensure the robustness of our results and to provide additional insights. First, we examine whether analysts' innovation-related questions are also associated with patent applications, an outcome of firms' innovation activities. We find that analysts' questions are positively associated with both the number of future patents applications and the number of patents granted in the future. Moreover, consistent with the knowledge spillover hypothesis, we find that when a firm has site visits with analysts asking questions about innovation, the firm tends to cite more patents of industry peers in its future patent applications. Second, we find that analysts' tendency to ask questions related to innovation is systematically affected by firm characteristics and their information acquisition costs. For example, we find that analysts are more likely to ask questions about a firm's innovation activities when they are geographically closer to or have highspeed rail access to the firm and when there is news coverage about the firm's innovation activities prior to site visits.

This paper contributes to literature in several ways. First, it contributes to the innovation literature by documenting a mechanism through which analysts can influence corporate innovation – asking questions about corporate innovation during site visits. Complementing prior research on the effect of analyst coverage on corporate innovation (Derrien & Kecskes, 2013; He & Tian, 2013; Guo et al., 2019), we focus on the specific actions taken by analysts that can affect corporate innovation. In addition, by focusing on analysts' questions during site visits, we provide direct evidence on how the knowledge spillover occurs. While analysts may not have incentives to reveal their private information through public interactions with management (e.g., conference calls), our results suggest that site visits offer a quasi-private venue for analysts to share (consciously or subconsciously) their unique insights on industry peers' innovation with the firm's management. In addition, while Martens and Sextroh (2021) document that analysts can play a role in knowledge spillover, we extend Martens and Sextroh (2021) by focusing on analysts' questions during site visits, examining a setting where analysts have stronger incentives to reveal their private information on corporate innovation, and providing direct evidence on *how* analysts' role in knowledge spillover affects firms' future innovation.

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.[1] The existing evidence on analysts' effect on corporate innovation is also mixed. On the one hand, greater analyst coverage may result in more innovation if analysts, as information intermediaries, help capital market participants better understand and interpret firms' investments in R&D (e.g., Derrien & Kecskes, 2013; Guo et al., 2019; He et al., 2023). On the other hand, greater analyst coverage may lead firms to cut R&D expenditures if it increases the pressure on management to meet analysts' earnings expectations (e.g., He & Tian, 2013). By focusing on analysts' innovation-related questions during site visits, our paper contributes to the debate by documenting a unique setting where analysts can share information with managers through their inquiries, shedding light on the intricate roles that analysts play in their influence 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 et al., 2016; Bowen et al., 2018; Han et al., 2018; Cheng et al., 2019). We contribute to this stream of research by analyzing the content of site visit transcripts and showing that the information flow during site visits occurs both ways, such that the questions asked by

[1] For example, see Yu (2008), McInnis and Collins (2011), Chen et al. (2015), Irani and Oesch (2016), Chapman and Green (2018), To et al. (2018), Ayres et al. (2019).

[2] Chapman and Green (2018) document that analysts' questions about forward-looking information affect the likelihood of managers providing earnings guidance in future periods, consistent with firms providing voluntary disclosure when there is a greater demand for such information. However, it is not obvious from their results whether analysts' questions about innovation activities affect firms' R&D and patent applications, because analysts usually do not forecast R&D expenditures or patent activities. In addition, we focus on the real activities – R&D investments and patent applications, not the disclosure of such activities as in Chapman and Green (2018).

analysts have an incremental role in shaping corporate innovation.[3]

2 | INSTITUTIONAL BACKGROUND AND RELATED RESEARCH

2.1 | Corporate site visits in China: Institutional background and related research

Corporate site visits refer to investors' trips to a firm's headquarters and its production facilities. During site visits, sell-side analysts, institutional investors, and other visitors have the chance to talk to corporate employees and visit corporate facilities. In China, site visits are usually initiated by investors; firms occasionally invite institutional investors, sell-side analysts, and journalists to visit, typically in the short period after announcing earnings or important corporate events such as mergers and acquisitions, rights offerings, and seasoned equity offerings. Investors who want to request site visits to a specific firm need to file an application form and sign an agreement to comply with the visited firm's corporate policies on site visits.

Prior research (e.g., Cheng et al., 2016; Bowen et al., 2018; Cheng et al., 2019) provides detailed discussions about corporate site visits. As discussed in Cheng et al. (2016), visitors' requests for site visits are usually accommodated by firms. In Article 41 of the "Guidelines of Investor Relations Management," the SZSE states that "Listed companies should try to accommodate the request from investors, analysts, and fund managers to visit company headquarters and project sites to the greatest extent." It further emphasizes in the guidelines that "Listed companies should arrange the site visits properly so that visitors may better understand the companies' business and operational situations." If the requested visit dates are in a sensitive

[3] Our paper is related to Jiang and Yuan (2018), who document a positive association between the *occurrence* of institutional investors' site visits and firms' corporate innovation. However, our paper differs from Jiang and Yuan (2018) in two ways. First, we focus on the *mechanism* through which analysts can influence corporate innovation, analysts' questions on corporate innovation during site visits. Unlike Jiang and Yuan (2018), our focus is not the occurrence of site visits per se, but rather analysts' questions during site visits conditional on the occurrence of site visits. Second, our results hold after controlling for the number of site visits, thus institutional investors' participation in site visits. In addition, we document that the participation by analysts in site visits with innovation-related questions has a positive incremental effect on corporate innovation over others' participation.

period, such as the blackout periods before earnings announcements and other important corporate announcements, firms usually advise an alternative date for the visit.

A typical site visit consists of a presentation by the managers, a Q&A session, and a field tour of corporate facilities. Board secretaries, who are the de facto investor relations managers in Chinese firms, accompany the visitors during most site visits. A unique feature of site visits is that visitors can observe firms' operations and research facilities and can thus obtain first-hand and timely information about firms' operations and research activities. Firms are also required to disclose the occurrence of site visits in a timely manner after 2012, and more than 69% of firms disclose the meeting agendas within two days after site visits. In our sample, each site visit has an average of 7.65 external participants and the average number of questions asked is 7.60. The most frequently discussed topics in the Q&A session include operating activities, corporate investment, management forecasts of future business, and financing activities.

2.2 | Review of the related literature on analyst coverage and innovation

In terms of site visit, previous research has studied how investors and analysts benefit from site visits. For example, Cheng et al. (2016) and Han et al. (2018) find that analysts experience an improvement in forecast accuracy after conducting site visits. Bowen et al. (2018) and Cheng et al. (2019) document significant abnormal returns after corporate site visits. While Cheng et al. (2019) find that the market reaction is partially driven by mutual funds' trading after site visits, Bowen et al. (2018) document an increase in insider trading around site visits.

Prior studies document that analyst coverage is associated with both firms' investments in innovation and their outcomes (e.g., Derrien & Kecskes, 2013; He & Tian, 2013; Guo et al., 2019; He et al., 2023). Focusing on patents, He and Tian (2013) find that compared with firms with low analyst coverage, those with high analyst coverage file fewer patents and have fewer patent citations. Focusing on R&D expenditures, Derrien and Kecskes (2013) find that firms with a drop in analyst coverage as a result of brokerage closures and mergers experience a decrease in R&D expenditures. This finding is consistent with that of Barth et al. (2001), who document a positive association between analyst coverage and R&D expenditures. More recently, examining different 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. Their results suggest that although analyst coverage may pressure managers to cut R&D in the short run, it leads to more investments in the long run.

Overall, prior studies examine the association between analyst coverage and the level of corporate innovation activities. Complementing these studies, this paper examines the *actions* taken by analysts that can affect corporate innovation – asking questions about corporate innovation during site visits. While analyst coverage provides a broad view of which firms are affected by analysts, it is through their questions and actions that their value emerges. By examining analysts' actions, we gain a richer understanding of their role in influencing firms' innovation and offer more actionable insights for investors and companies alike.

3 | HYPOTHESIS DEVELOPMENT

Financial analysts are key information intermediaries in the capital markets. In this section, we discuss why their innovation-related questions during site visits can positively affect firms' innovation activities via a knowledge spillover effect. The knowledge spillover effect is well documented in the economics literature (e.g., Aghion & Jaravel, 2015). For example, Jaffe et al. (2000) find that knowledge spillovers can occur from innovators to other parties, including competitors. Prior research indicates that the spillover effect can be facilitated by financial intermediaries. For example, Luong et al. (2017) find that foreign institutional investors can facilitate knowledge spillovers from high- to low-innovation economies.

Analysts possess a unique advantage in this regard, as they typically cover multiple firms within the same industry. This affords them access to information about various firms' innovation activities through networks with firm managers, public information processing, and active information acquisition related to innovation endeavors. Consequently, analysts often possess more comprehensive information about the innovation landscape of the industry than individual firms' managers. This information is particularly valuable because it is often proprietary and not readily disclosed by firms. Supporting this perspective, Martens and Sextroh (2021) find that a firm is more likely to cite another firm's patents when both firms are covered by the same analyst. This valuable feedback from analysts can assist managers in refining their investment decisions, thus giving rise to what we term the "knowledge spillover hypothesis."

One mechanism through which the knowledge spillover effect can affect corporate innovation is analysts asking questions on innovation during the Q&A session with managers as part of site visits. When analysts engage with managers, they may raise inquiries about a firm's research and development efforts, technology adoption, and innovation strategy. In response to analysts' questions about these topics, firms need to articulate and clarify their innovation objectives and roadmaps. Analysts' questions on a firm's R&D efforts can also yield insights that inadvertently shed light on its industry peers' innovation activities and competitive strategies. As a result, the questions may prompt firms to reconsider or refine their approaches, explore new opportunities, or collaborate with external partners. In addition, when analysts inquire about emerging industry trends, competitive dynamics, or disruptive technologies, they can inspire firms to adapt and innovate proactively. That is, during the Q&A sessions of site visits, analysts can share information about competitors' innovation activities.

Knowledge spillovers through analysts are more likely to occur during site visits than in other venues because the site visit transcripts do not reveal the identity of the specific individual who asks a particular question. Analysts are thus less concerned about sharing competitors' innovation activities (either consciously or subconsciously) because doing so is less likely to damage their relationships with the focal firm's peers that they cover. 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.[4] During the same site visit, T&S was also asked whether their products are substitutes for products offered by a competitor, TFC Optical, and whether the company has competed or collaborated with TFC.[5] Analysts' sharing may thus prompt firms to increase their own innovation activities owing to concerns about the enhanced competition brought about by competitors' innovation activities.

In summary, the above discussion suggests that analysts' questions about innovation during site visits can have a positive effect on corporate innovation activities. Thus, we state our hypothesis as follows:

H1: Analysts' questions about corporate innovation during site visits have a positive impact on corporate innovation activities.

A maintained assumption underlying the above argument is that firms under-invest in innovation due to agency problems and/or potential undervaluation of innovation. To the extent

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[4] The English translation of the quote is as follows: "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?"

[5] The English translation of the quote is as follows: "Are the company's ceramic ferrule and ceramic sleeve products from TFC Optical substitutes in applications? Has the company competed or collaborated with TFC?"

that firms undertake the optimal level of investments without the influence from analysts, the above argument might not hold. Therefore, whether analysts' questions on innovation during site visits lead to an increase or decrease in innovation is an empirical question.

4 | SAMPLE AND RESEARCH DESIGN

4.1 | 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 and news report 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. Because our focus is on how analysts' questions during site visits affect corporate innovation, we require each firm-year to have at least one site visit. We also exclude firms in the financial industry. We end the sample period in 2019 to avoid the confounding effect of Covid-19 starting in 2020. After removing observations with missing values for our variables and visitor information, the final sample includes 39,793 site visits, 7,284 firm-years, and 1,995 unique firms. Table 1 provides the sample selection process. Our analyses are conducted at the firm-year level.

[Insert Table 1]

4.2 | Measurement of corporate innovation

We examine the effect of analysts' questions about firms' innovation activities by analyzing the change in firms' future R&D expenditures, the input measure of corporate innovation activities. We also examine the change in patent applications, the output measure, in an additional analysis because the two measures complement each other (e.g., Autor et al., 2020).

We focus on the change in R&D expenditures in year t+1 ($\Delta R\&D_{it+1}$) to investigate the

Granger causal effect of analysts asking questions about innovation in year *t*. In addition, 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., Guo et al. 2019; Dai et al., 2021), $\Delta R\&D_{it+1}$ 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 the average revenue in years *t*−1 and *t*−2 for firm *i*.[6] Then, we multiply this value by 100 for ease of result 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. As reported in Table 2, on average, firms increase *R&D* by 3.1% of sales over the sample period.

[Insert Table 2]

4.3 | Measurement of analysts asking questions about corporate innovation during site visits

To capture analysts asking questions about corporate innovation during site visits, we 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.[7]

We use the term "site visits with analysts asking questions about corporate innovation" for

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[6] Since 2007, firms have been required to disclose R&D expenditures under China Accounting Standards. Thus, we assume that a firm does not have R&D expenditures in a year if it reports zero R&D or has missing data on R&D.
[7] To check the accuracy of this approach, we randomly select 500 site visits in 2020, which is out of the sample period. We then read all questions asked during these site visits and manually classify them as innovation-related or non-innovation-related. Based on our reading of the questions, we find that the keyword-based approach is accurate in identifying *site visits* with analysts asking questions about corporate innovation at the 92.4% level and in identifying *firm-years* having site visits with analysts asking innovation-related questions at the 91.7% level.

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. We obtain the same inferences in an untabulated analysis when we restrict our analysis to a subsample of site visits with high analyst participation rate (i.e., when the number of analyst participants is above the sample median).

We then 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 is equal to 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*, and zero otherwise. $AnalystAsk\_R_{it}$ is the ratio of the number of site visits in which analysts 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 Table 2, about 56.3% of the firm-years have at least one site visit during which analysts ask innovation-related questions. 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. That is, we are essentially comparing (1) site visits with analysts and questions on innovation (i.e., *AnalystAsk_D* = 1) and (2) site visits with analysts but no questions on innovation (i.e., *AnalystAsk_D* = 0).[8] The distinction between the two groups is therefore the occurrence and intensity of innovation-related questions conditional on the existence of site visits. At the firm-year level, analysts ask innovation-related questions in approximately 28.2% of the site visits.

4.4 | Research design

[8] Of the 3,181 observations with *AnalystAsk_D* being zero, the majority (2,854 observations) have site visits participated by analysts but without questions on innovation. The other observations either have site visits with innovation questions but no analysts participating (106 observations) or have site visits with neither analyst participation nor innovation questions (221 observations). Dropping the last two groups leads to the same inferences.

We use the following regression model to investigate the impact of analysts' questions about corporate innovation on corporate innovation:

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

where subscripts *i*, *t*, and *j* refer to firm *i*, year *t*, and industry *j* to which firm *i* belongs, respectively. $\Delta R\&D_{it+1}$ is as defined above.[9] The independent variable of interest is $AnalystAsk_{it}$, which is $AnalystAsk\_D_{it}$ or $AnalystAsk\_R_{it}$. H1 predicts a positive coefficient on $AnalystAsk_{it}$.

It is possible that analysts ask questions regarding corporate innovation during site visits because they are aware of a firm's plan on *future* innovation activities from news. To address this concern, we control for the number of news reports mentioning the firm's innovation activities ($InnoNews_{it}$). $InnoNews_{it}$ is defined as the natural logarithm of one plus the average number of news reports about firm *i* that mention any of the keywords for innovation in the 60 calendar days prior to each site visit in year *t*.[10] The data of news reports are collected from the Chinese Research Data Services Platform.

Following the innovation literature (He & Tian, 2013; Guo et al., 2019), we control for firm characteristics that can 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 is equal to 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. $CASH_{it}$ is cash divided by total assets, PPE_{it} is property, plant, and equipment divided by total assets, $CAPEX_{it}$ is capital

[9] Examining the change in R&D expenditures is appropriate in our setting because $AnalystAsk_{it}$ captures an event and thus a shock to firms' decisions on corporate innovation. That is, we are interested in whether analysts' questions on innovation during site visits induce managers to *change* their behavior in corporate innovation. Nevertheless, in an untabulated test, we conduct a level regression, and the inferences remain the same.
[10] In an untabulated analysis, we further control for news reports about firms' innovation activities measured in the 60 calendar days *after* site visits, during which information on firms' upcoming innovation activities that analysts might have is likely to be covered by the press. Our inferences remain the same.

expenditure divided by total assets, and $InstOwn_{it}$ is the ownership of institutional investors. HHI_{jt} is the Herfindahl–Hirschman index for industry j to which firm i belongs. $KZindex_{it}$ is the Kaplan–Zingales (KZ) index, which measures a firm's financial constraints. All control variables are measured in year t except for lagged R&D, which is measured in years t–1 and t–2. The Appendix provides detailed variable definitions. Lastly, we include industry and year fixed effects to control for time-invariant industry characteristics and time trends. To minimize the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. We calculate t-statistics based on standard errors adjusted for clustering at the firm level.

As reported in Table 2, an average firm has 10.3 innovation-related news reports, 6.6 analysts following it, a book value of assets of 9.452 billion yuan, an age of 8.0 years, leverage of 38.7%, a book-to-market ratio of 0.35, a 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. The average Herfindahl index at the industry level is 0.087.

Appendix S1 of the Internet Appendix reports the correlations between the variables used in the main analyses. The magnitudes of the correlation coefficients are generally small. An analysis of the variance inflation factor (VIF) indicates that there is no multicollinearity problem because all VIFs are smaller than 3.70.

5 | MAIN ANALYSES

5.1 | Baseline results

Table 3 reports the baseline results for the analysis of $\Delta R\&D_{it+1}$. In Column (1), we find that the coefficient on $AnalystAsk\_D_{it}$ is 0.378 and significantly positive at the 1% level. This result is consistent with analysts' innovation-related questions being positively associated with the change 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 questions experience an increase in R&D expenditures of 0.378% of sales in the following year, or a relative increase of 6.7% (= 0.378/5.642) of the sample standard deviation of $\Delta R\&D_{it+1}$. 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.

[Insert Table 3]

The results using the ratio variable presented in Column (2) of Table 3 lead to the same inferences. We find that the coefficient on $AnalystAsk\_R_{it}$ is significantly positive at the 1% level. The magnitude of the coefficient (0.946) indicates that a one-standard deviation increases in the proportion of site visits in which analysts ask innovation-related questions results in an increase in R&D expenditures of 0.319% of sales (= 0.946 × 0.337) in the following year, or a relative increase of 5.7% (= 0.319/5.642) of the sample standard deviation of $\Delta R\&D_{it+1}$.

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

Overall, the results in Table 3 suggest that analysts' questions about firms' innovation-related activities are associated with an increase in firms' innovation activities.[11] These results are consistent with H1 on the knowledge spillover hypothesis.

5.2 | Addressing endogeneity

Whether analysts ask questions about corporate innovation during site visits can be

[11] In an untabulated test, we control for the proportion of fund participants in site visits and find the same results, suggesting that our results are unlikely to be driven by the knowledge spillover from institutional investors.

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 issue in the main analyses by using lagged $AnalystAsk_{it}$ to explain future R&D expenditures and by controlling for press news on corporation innovation ($InnoNews_{it}$). In addition, analysts might ask innovation-related questions if the managers share about their future innovation activities during the site visit. Below, we conduct additional tests to address these endogeneity concerns.

5.2.1 | Shock to *AnalystAsk*

Our first approach to address endogeneity is to identify shocks to the likelihood of analysts asking questions on innovation. Specifically, we use the initial coverage of an innovation-expert analyst as a shock to the likelihood of analysts asking innovation-related questions during site visits. The innovation-expert analyst's initial coverage decision is unlikely to be correlated with the firm's *future* innovation activities, which the analyst is unlikely know about before she starts to cover the firm, satisfying the exclusion criterion. At the same time, an innovation expert's initial coverage can increase the likelihood of analysts' questions on corporate innovation during site visits, satisfying the relevance criterion. Like Cen et al. (2021), we consider an analyst as an innovation expert if she has had more exposure to innovation-related questions during site visits in the past. Specifically, an analyst is considered an innovation expert if more than half of the site visits in which the analyst participated in year $t-1$ had questions related to innovation. We then construct an indicator variable, $InnoExpert\_Cover_{it}$, which is equal to one if an innovation-expert analyst does not cover firm i in years $t-1$, $t-2$, and $t-3$, but covers it in year t.

We first validate the relevance of the shock by examining the effect of having an innovation-expert analyst covering a firm on the likelihood of analysts asking questions about innovation in the site visits to the firm using the following equation:

$$AnalystAsk_{it} = \beta_0 + \beta_1 InnoExpert\_Cover_{it} + \gamma Controls_{it} + YEAR_t + INDUSTRY_j + \varepsilon_{it} \quad (2)$$

Panel A of Table 4 presents the results from this analysis. Consistent with innovation-expert analysts being more likely to ask innovation-related questions, we find a significantly positive coefficient on $InnoExpert\_Cover_{it}$ (t = 3.98 and 2.17 in the analyses of $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$, respectively).

[Insert Table 4]

We then test whether a firm is indeed more likely to increase its R&D expenditures in the future when an innovation-expert analyst initiates coverage of the firm. We use the following regression model to investigate the impact of the initial coverage by an innovation-expert analyst on future corporate innovation:[12]

$$\Delta R\&D_{it+1} = \beta_0 + \beta_1 InnoExpert\_Cover_{it} + \gamma Controls_{it} + YEAR_t + INDUSTRY_j + \varepsilon_{it+1} \quad (3)$$

Panel B of Table 4 presents the results from this analysis. Consistent with our main results, we find a significantly positive coefficient on $InnoExpert\_Cover_{it}$ (t = 2.77). The coefficient on $InnoExpert\_Cover_{it}$ (1.066) implies that the initial coverage of an innovation-expert analyst is associated with an increase in $\Delta R\&D_{it+1}$ by 18.9% (= 1.066/5.642) of its standard deviation.

One might be concerned that the above results are driven by brokerage houses' decisions to send innovation experts to cover a firm when they expect industry-wide technological changes. While this alternative explanation might be able to explain one-year-ahead changes in R&D expenditures, it is less likely to explain two- and three-year-ahead changes in R&D expenditures because brokerage houses cannot predict industry-wide changes two or three years in the future. An untabulated test indicates that $InnoExpert\_Cover_{it}$ is positively correlated with two- and

[12] Model (3) is based on the reduced form of the 2SLS, which is applicable when there is one instrumental variable for one endogenous variable (Schmidheiny, 2023). The inferences remain the same when we conduct a 2SLS regression analysis using $InnoExpert\_Cover_{it}$ as the instrumental variable.

three-year-ahead R&D expenditures. In addition, if the alternative argument is correct, we should expect $InnoExpert\_Cover_{it}$ to explain industry peers' R&D expenditures because the brokerage houses' decision to send innovation expert to cover firm *i* is based on their expectation of industry-wide technological changes. However, we do not find such results.

In sum, our inferences remain the same when we use the initial coverage of an innovation-expert analyst as a shock to the likelihood of analysts asking innovation-related questions during site visits.

5.2.2 | Subsample analysis

While a typical site visit only includes the Q&A session, some begin with a manager presentation before the Q&A. Therefore, it is possible that analysts ask questions about innovation when the hosting firm presents its future R&D plans before the Q&A section during site visits. To address this concern, we re-estimate Equation (1) using a subsample of firms where innovation-related words appear in analysts' questions first (i.e., there are no innovation-related words in the management presentation preceding analysts' questions). To the extent that analysts inquire about innovation first, their questions are unlikely to be prompted by managers' presentations about the firm's future innovation activities.

Table 5 presents the results from this subsample analysis. We find that the coefficient on $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$ (t = 2.56 and 3.67, respectively). Overall, our inferences remain the same when we use the subsample with innovation-related words first appearing in analysts' questions.[13]

[Insert Table 5]

5.2.3 | Controlling for firm fixed effects

[13] We also replicate the tests after controlling for the number of innovation-related words in managers' presentations during site visits using the full sample. The inferences based on this untabulated test remain the same.

To control for time-invariant firm characteristics that might affect both the likelihood of analysts asking questions on innovation and firms' future innovation, we replace industry fixed effects with firm fixed effects. To ensure that there is enough variation within firms, we restrict the analyses to firms with at least six observations during the sample period. Table 6 reports the results from this analysis. We continue to find significantly positive coefficients on $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$ (t = 1.95 and 1.83, respectively).

[Insert Table 6]

Overall, our inferences remain the same after addressing potential endogeneity using various approaches. Nevertheless, we admit that we cannot fully rule out the possibility that the documented results are affected by endogeneity.

5.3 | Cross-sectional analyses of the knowledge spillover hypothesis

In this section, we conduct a number of cross-sectional analyses to further strengthen our inferences. We identify cases where innovation knowledge spillovers are likely stronger and then test whether our results are more pronounced in such cases. First, sell-side analysts specialize by industry and understand the factors that affect a firm's performance relative to its industry peers (Kadan et al., 2012). 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 as a result, have more information about innovation activities in other firms. Second, managers are more likely to benefit from analysts' knowledge about competitors' innovation activities if they have similar technology as the focal firm (Byun et al., 2021). Thus, the effect of analysts' innovation-related questions on corporate innovation should be stronger when the technology of the focal firm and that of peer firms are more closely related. Third, the innovation knowledge spillover effect is likely stronger when analysts participating in site visits are experts in innovation because they have a better understanding of technological development and the innovation trends for the industry and can better share such information with firm management. We thus expect that the effect of analysts' innovation-related questions on corporate innovation is stronger when more innovation-expert analysts participate in the site visits with questions on innovation.

To test these predictions, we construct three variables: $IndCoverage_{it}$, $TechSimilarity_{it}$, and $InnoExpertAsk_{it}$. $IndCoverage_{it}$ is an indicator variable that is equal to 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 is equal to one if the focal firm's technological similarity with its industry peers is above the sample median, and zero otherwise. $InnoExpertAsk_{it}$ is an indicator variable that is equal to one if there is at least one site visit with innovation-related questions in the presence of an innovation-expert analyst, and zero otherwise. See Appendix for details on the construction of these variables. Then, we interact $AnalystAsk_{it}$ with these three variables separately and add them to the regression model. We expect positive coefficients on the interaction terms if analysts' questions better help diffuse knowledge regarding firms' innovation activities in the above-discussed cases.

Table 7 presents the results from this analysis. We first discuss the results using $IndCoverage_{it}$ in Panel A. We find that the coefficients on $AnalystAsk\_D_{it} \times IndCoverage_{it}$ and $AnalystAsk\_R_{it} \times IndCoverage_{it}$ are significantly positive (t = 2.14 and 1.93, respectively). These results suggest that the impact of analysts' questions on firms' future R&D expenditures is greater when visiting analysts cover more firms in the same industry.

[Insert Table 7]

In Panel B, where we interact $AnalystAsk_{it}$ with $TechSimilarity_{it}$, we find a significantly positive coefficient on $AnalystAsk\_D_{it} \times TechSimilarity_{it}$ in Column (1). This result suggests that the impact of analysts' questions on firms' future R&D expenditures is greater for firms that have more similar technologies as industry peers. The coefficient on $AnalystAsk\_R_{it} \times TechSimilarity_{it}$ in Column (2) is also positive, although not significant at conventional levels.

In Panel C, where we interact $AnalystAsk_{it}$ with $InnoExpertAsk_{it}$, we find significantly positive coefficients on both $AnalystAsk\_D_{it} \times InnoExpertAsk_{it}$ and $AnalystAsk\_R_{it} \times InnoExpertAsk_{it}$ (t = 2.17 and 2.20, respectively).[14] The positive coefficients on the interaction terms suggest that the impact of analysts' questions on firms' future R&D expenditures is greater when an innovation-expert analyst is present, presumably because she can share her expertise on industry-specific technologies and trends.

Overall, the results from these tests suggest that analysts' innovation-related questions have a positive impact on corporate innovation through a knowledge spillover effect.[15]

6 | ADDITIONAL ANALYSES

6.1 | Test of alternative explanations – Informational role of analysts

The positive association between analysts' questions and firm innovation can also be due to the information role of analysts documented in the literature. Analysts can help reduce the undervaluation problem arising from R&D investments and thus induce managers to engage in more innovation activities. In the context of site visits, analysts acquire additional information regarding corporate innovation activities when they ask questions about innovation (e.g., Derrien

[14] We do not include the main effect of $InnoExpertAsk_{it}$ because it is set as zero when $AnalystAsk_{it}$ is equal to zero.
[15] In an untabulated test, we include all the variables used in the cross-sectional analyses and find that the coefficient on $AnalystAsk_{it}$ is almost identical to that in the main analysis.

& Kecskes, 2013). They can then report on and help interpret 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. To examine whether the information role of analysts explain our results, we identify firms with lower information environmental quality, for which analysts' information role is more important. If the information role of analysts explains our results, the positive association we document should be stronger for firms with a poorer information environment, because analysts can better disseminate information about firms' innovation activities through their inquiries during site visits to help reduce the information asymmetry.

As commonly used in the literature, we use the level of analyst coverage, firm size, and media coverage to capture a firm's information environment quality (Healy & Palepu, 2001; Ahn et al., 2019). As such, we construct three indicator variables: (1) AC_L_{it}, an indicator variable for firms with analyst coverage below the sample median, (2) $Size\_L_{it}$, an indicator variable for firms with total assets below the sample median, and (3) $NewsCov\_L_{it}$, an indicator variable for firms with the number of news reports below the sample median. We then add the interaction terms of $AnalystAsk_{it}$ with AC_L_{it}, $Size\_L_{it}$, and $NewsCov\_L_{it}$ to the regression model separately 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 8 presents the results from this analysis. We first discuss the results using AC_L_{it} in Panel A. We find that the coefficients on $AnalystAsk\_D_{it} \times AC\_L_{it}$ and $AnalystAsk\_R_{it} \times AC\_L_{it}$ are negative and significant at the 1% level. These results suggest that the positive impact of analysts' questions on innovation is weakened for firms with low analyst coverage, opposite to the prediction based on the information role of financial analysts.[16]

[Insert Table 8]

In Panel B, where we use $Size\_L_{it}$ to proxy for the firm's information environment, we also find significantly negative coefficients on $AnalystAsk\_D_{it} \times Size\_L_{it}$ and $AnalystAsk\_R_{it} \times Size\_L_{it}$. Finally, in Panel C, where we use $NewsCov\_L_{it}$, we also find significantly negative coefficients on $AnalystAsk\_D_{it} \times NewsCov\_L_{it}$ and $AnalystAsk\_R_{it} \times NewsCov\_L_{it}$, consistent with the association between analysts' questions and innovation being weakened for firms with low news coverage.

Overall, these results are *inconsistent* with analysts' information dissemination role as an alternative explanation for our results.

6.2 | Test of alternative explanations – Monitoring role of analysts

Another alternative explanation for the positive impact of analysts' questions that we document is the monitoring role of analysts. Prior research (e.g., Yu, 2008; Chen et al., 2015) finds that analysts can play a monitoring role by reducing agency costs. To the extent that underinvestment in corporate innovation is a manifestation of agency costs, analysts' innovation-related questions can positively affect corporate innovation by reducing agency costs. During their interactions with management during site visits, analysts can directly inquire about firms' investments in innovation, and executives must be prepared to answer such questions. If they underinvest in innovation, they might feel the pressure from analysts to invest more. Thus, the monitoring role of analysts implies that the positive association between analysts asking innovation-related questions and firms' future innovation should be stronger when a firm has

[16] One possible explanation for the result is that fewer analysts ask questions related to innovation during site visits when analyst coverage is lower, and thus the knowledge spillover effect is weaker. Similar explanation applies to smaller firms (*Size_L*) and firms with less media coverage (*NewsCov_L*).

higher agency costs.

To test whether the monitoring role of analysts explains our results, we rely on prior research and use the ownership of large shareholders and board effort to capture the extent of firms' agency costs (e.g., Vafeas, 1999). The extent of agency costs is higher for firms with lower large shareholder ownership and lower board effort. As such, we construct two variables to capture the level of agency costs in a firm, (1) Own_L_{it}, an indicator variable for firms with the large shareholder ownership lower than the sample median, and (2) $BoardMeet\_L_{it}$, an indicator variable for firms with the frequency of board meetings below the sample median. We then add the interaction terms of $AnalystAsk_{it}$ with these two proxies for agency costs separately to the regression model. If analysts' questions help monitor managers who are likely to underinvest in innovation due to agency problems, we expect positive coefficients on the interaction terms.

Table 9 presents the results from this analysis. We first discuss the results using Own_L_{it} in Panel A. Contrary to the monitoring hypothesis, the coefficients on both $AnalystAsk\_D_{it} \times Own\_L_{it}$ and $AnalystAsk\_R_{it} \times Own\_L_{it}$ are negative, although insignificant at conventional levels. In Panel B, where we interact $AnalystAsk_{it}$ with $BoardMeet\_L_{it}$, we find a negative coefficient on $AnalystAsk\_D_{it} \times BoardMeet\_L_{it}$, significant at the 5% level.

[Insert Table 9]

Overall, the results from these tests are *inconsistent* with the monitoring role of analysts and suggest that our results are unlikely to be explained by analysts' questions helping to alleviate the underinvestment problem arising from agency costs.[17]

6.3 | Analysts' questions and future patent applications

[17] The monitoring hypothesis also predicts that analysts are more likely to raise innovation-related questions when the company's R&D investment is below the industry average. However, we find the opposite in an untabulated analysis, further suggesting that our results cannot be explained by the monitoring hypothesis.

In this section, we examine whether our results are robust to using patent applications, an output measure of innovation activities. Patent applications indicate the occurrence of innovations resulting from innovation activities. We do not examine patent applications in the main analysis because they can underestimate the firm's innovation activities. Some innovations might not be codified in patents (e.g., trading secrets) or considered important enough to be filed as patents. Because it takes time for R&D investments to generate patentable outputs, we examine innovation outcomes in year t+3 to capture the long-term effects of these investments. To construct the output measures of innovation, we first calculate the change in the number of patent applications in year t+3 ($\Delta Patent_{it+3}$), which is calculated as the difference between the number of patent applications in year t+3 and the average number of patent applications in years t−1 and t−2 for firm i. Then, we take the natural logarithm of this variable, $Ln\Delta Patent_{it+3}$, to address the skewness of the variable. One benefit of examining the total number of patent applications is that it is less affected by truncation issues.[18] However, the disadvantage of using the number of patent applications is that it does not consider the quality of patent applications because not all patent applications are granted eventually.[19] To capture the quality of grant applications, we use a similar approach to calculate the change in the number of patent applications in year t+3 that are later granted, $Ln\Delta Grant_{it+3}$, as commonly done in the literature (Guo et al., 2019). As reported in Panel A of Table 10, the average number of patent applications

[18] There are three types of patents in China: invention, utility model, and design. We include all patents in the analyses. In an untabulated test, we focus on invention patents only and obtain the same inferences. Separately, in contrast to the U.S., where only the information about patent applications that are eventually granted is available, in China, we can observe all patent applications, granted or not.

[19] We do not use future patent citations to capture innovation quality because the citation data is truncated. Lerner and Seru (2022) document that the future citations of patents can be subject to a truncation bias for up to 10 years. While the number of patent applications and patent grants are also subject to truncation biases, the issue is less severe. In addition, to address the truncation issue, we restrict our sample period for this analysis to 2013-2017, with the last year of patent applications and patent grants measured in 2020, when the number of patent applications and patent grants peaked (untabulated). The inferences remain the same.

and patent applications eventually granted increases by 51.5 and 31.8, respectively, in year t+3.

We then use the same research design to examine the effect of analysts' questions on the number of patent applications and patents granted, and report the results in Panel B of Table 10. Columns (1) and (2) report the results from the analysis of $Ln\Delta Patent_{it+3}$. In Column (1), we find that the coefficient on $AnalystAsk\_D_{it}$ is 0.218 and significantly positive at the 1% level (t = 2.68). This result is consistent with analysts' innovation-related questions being positively associated with an increase in patent applications in the future. In terms of economic significance, the magnitude of the coefficient (0.218) 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 in the year t+3 by 8.0% (= 0.218/2.722) of the sample standard deviation. The results using the ratio variable are similar, albeit statistically weaker.

Columns (3) and (4) report the results from the analysis of $Ln\Delta Grant_{it+3}$, and the inferences remain the same.

If analysts facilitate innovation knowledge spillover across firms, then firms are more likely to cite other firms' patents when analysts ask questions related to innovation during site visits. To test whether this is the case, we measure the cross-citations of a firm's patent applications – the number of patents from industry peers cited by the focal firm in its patent applications. We hence construct a new variable, $Ln\Delta CiteInd_{it+3}$, which is the natural logarithm of the percentage change in the citation number, which is the ratio of the number of citations of industry peers' patents by firm i's patent applications from years $t-1$ and $t-2$ to year t+3.[20] We then use the same research design to examine the effect of analysts asking questions on innovation on patent cross-citations and report the results in Panel C of Table 10. In Column (1),

[20] We use the percentage change in the cross-citations of industry peers' patents to ensure that the measure is not confounded by the number of patent applications.

we find that the coefficient on $AnalystAsk\_D_{it}$ is significantly positive at the 10% level (t = 1.82). This result is consistent with analysts' innovation-related questions being positively associated with an increase in citations of industry peers' patents by the focal firm's patent applications in the future. The coefficient on $AnalystAsk\_D_{it}$ (0.036) implies a relative increase of 6.0% (= 0.036/0.596) of the standard deviation of $Ln\Delta CiteInd_{it+1}$.

In an additional test, to better document the knowledge diffusion of the analysts, we further define common analyst as the analysts who cover both the focal firm and an industry peer firm (i.e., issuing earnings forecasts or recommendation or conducting site visits). We examine the effect of common analyst participants asking about innovation during site visits on the focal firm's patent citation from industry peer firms that share the same common analysts. In an untabulated test, we find a significantly positive effect of common analyst participants asking innovation-related questions during site visits to a firm on the change in its citations of industry peers' patents in the future, supporting the knowledge spillover argument. We also conduct a placebo test to examine whether common analyst participants asking innovation-related questions during site visits explains the change in a firm's citations of patents of industry peers that *do not* share common analysts as the firm. Consistent with the knowledge spillover argument, we do not find any significant results from this test.

Overall, these results suggest that analysts' questions about firms' innovation-related activities help increase the quantity and quality of patent applications in the future. In addition, analysts' innovation-related questions also help increase the cross-citations of industry peers' patents, consistent with H1 on the knowledge spillover hypothesis.[21]

[21] Given that analysts' innovation-related questions facilitate knowledge spillover but not necessarily scientific breakthroughs, the innovation outcomes are likely to be incremental to existing technologies. Following prior research (Benner & Tushman, 2002), we classify patents into two categories: exploitative and exploratory, with the former being incremental innovation and the latter being scientific breakthroughs. Consistent with knowledge

[Insert Table 10]

6.4 | Determinant test of analysts' questions about innovation

We also explore the determinants of the likelihood of analysts' questions about firms' innovation-related activities. As discussed in detail in Appendix S2 and reported in Table S1 of the Internet Appendix, we find that analysts' tendency to ask questions related to innovation is systematically affected by firm characteristics and their information acquisition costs. Specifically, we find that analysts are more likely to ask questions about a firm's innovation activities when they are geographically closer to or have highspeed rail access to the firm and when there is news coverage about the firm's innovation activities prior to site visits. In addition, analysts are also more likely to ask questions about innovation when the firm's R&D expenditures in the prior year is higher, when the firm is smaller, younger, and more profitable, and when it has higher leverage and higher capital expenditures.

7 | CONCLUSION

While prior studies have examined the relation between analyst coverage and innovation, 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 applications in the following year. We hypothesize and find that this result is consistent with knowledge diffusion between firms, as the association is stronger when analysts cover more firms in the same industry, when firms share similar technologies, and

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spillover argument, we find in an untabulated analysis that $AnalystAsk_{it}$ is positively associated with exploitative patents, but not exploratory patents.

when the questions are asked in the presence of an innovation-expert analyst.

This paper contributes to the literature by providing direct evidence on the mechanism through which analysts affect corporate innovation – analysts' questions about innovation during site visits. Our findings suggest that analysts play a knowledge spillover role in shaping corporate innovation through their questions about firms' innovation activities.

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Appendix
Variable Definitions

Dependent variable	
$\Delta R\&D_{it+1}$	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.
Independent variables	
$AnalystAsk\_D_{it}$	Indicator variable for analysts asking questions about innovation, is equal to 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 visit 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., the 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*.
Control variables	
$InnoNews_{it}$	Natural logarithm of one plus the average number of news reports related to firm *i* that mention innovation-related keywords in the 60 calendar days prior to site visits in year *t*.
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 RMB 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 firm *i*'s profit, is equal to 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_{jt}	Herfindahl–Hirschman index of industry *j* 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 industry *j*.
$KZindex_{it}$	Kaplan–Zingales (Kaplan & Zingales, 1997) index of firm *i* in year *t*, calculated as follows. First, *KZ1* is equal to one if *cash flow/PPE* is lower than the sample median in year *t*, *KZ2* is equal to one if *Tobin's q* is higher than the sample median in year *t*, *KZ3* is equal to one if *Leverage* is higher than the sample median in year *t*, *KZ4* is equal to one if *Dividends/PPE* is lower than the sample median in year *t*, and *KZ5* is equal to 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: $$KZ_{it} = \alpha_0 + \alpha_1 cash\ flow_{it}/PPE_{it-1} + \alpha_2 Tobin's\ Q_{it} + \alpha_3 Leverage_{it} + \alpha_4 Dividends_{it}/PPE_{it-1} + \alpha_5 cash\ holdings_{it}/PPE_{it-1} + \varepsilon_{it}$$ Third, $KZindex_{it}$ for firm *i* in year *t* is the predicted value of *KZ* calculated using the estimated coefficients obtained from the second step.
Cross-sectional variables	
$IndCoverage_{it}$	Indicator variable for analysts' industry coverage, is equal to one if the average number of firms in the same industry followed by each analyst that conducts site visits to firm *i* in year *t* exceeds the sample median, and zero otherwise.
$TechSimilarity_{it}$	Indicator variable for technology spillovers, is equal to 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 et al. (2021), we first calculate the correlation between firm *i* and firm *j*'s patent composition as below. $$Techcorr_{ijt} = \frac{\boldsymbol{X}_{it}\boldsymbol{X}'_{jt}}{(\boldsymbol{X}_{it}\boldsymbol{X}'_{it})^{0.5}(\boldsymbol{X}_{jt}\boldsymbol{X}'_{jt})^{0.5}}$$ where $\boldsymbol{X}_{it} = (X_{i1t}, X_{i2t}, X_{i3t})$ is a vector denoting the proportion of patents in the three types: invention patents, utility model patents, and design patents, of firm *i* in year *t*. $\boldsymbol{X}_{jt}$ is defined similarly. We calculate technological spillover potential for firm *i* with industry peers in year *t* based on the weighted average of $Techcorr_{ijt}$: $$Tech\_spillover_{it} = \sum_{j=1}^{J} Techcorr_{ijt} \times RD_{jt}$$ where RD_{jt} 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 (other than firm *i*). A higher value of $Tech\_spillover_{it}$ indicates a larger technological spillover possibility of firm *i* with its industry peers in year *t*.
$InnoExpertAsk_{it}$	Indicator variable for the participation by innovation-expert analysts, is equal to one if there is at least one site visit with innovation questions participated by an innovation-expert analyst for firm *i* in year *t*, and zero otherwise. An analyst is referred to as an innovation-expert if more than half of the site visits in which the analyst participated had questions related to innovation in year *t*−1.
AC_L_{it}	Indicator variable for low analyst coverage, is equal to one if the number of analysts covering firm *i* in year *t* is below the sample median, and zero otherwise.
$Size\_L_{it}$	Indicator variable for low firm size, is equal to one if the total assets of firm *i* in year *t* is below the sample median, and zero otherwise.
$NewsCov\_L_{it}$	Indicator variable for low news coverage, is equal to one if the number of news reports about firm *i* in year *t* is below the sample median, and zero otherwise.
Own_L_{it}	Indicator variable for low large shareholder ownership, is equal to one if the ownership of the top 10 shareholders excluding the largest shareholder of firm *i* in year *t* is below the sample median, and zero otherwise.
$BoardMeet\_L_{it}$	Indicator variable low board meeting frequency, is equal to one if the number of board meetings of firm *i* in year *t* is below the sample median, and zero otherwise.
Variables used in other analyses	
$InnoExpert\_Cover_{it}$	Indicator variable that is equal to one if an innovation-expert analyst covers firm *i* in year *t* but did not cover firm *i* in years *t*−1, *t*−2 and *t*−3, and zero otherwise. An analyst is referred to as an innovation-expert if more than half of the site visits in which the analyst participated in year *t*−1 had questions related to innovation.

LnΔPatent$_{it+3}$	The natural logarithm of the change in patent applications by firm *i* in year *t*+3, calculated as $Ln\ (\Delta Patent_{it+3}+1)\ if\ \Delta Patent_{it+3} \geq 0, and\ -Ln(-\Delta Patent_{it+3}+1)\ if\ \Delta Patent_{it+3} < 0$. $\Delta Patent_{it+3}$ is calculated as $Patent_{it+3} - \frac{1}{2}(Patent_{it-1} + Patent_{it-2})$, where *Patent*$_{it}$ is the number of patent applications by firm *i* in year *t*.
LnΔGrant$_{it+3}$	The natural logarithm of the change in patent applications by firm *i* in year *t*+3 that are eventually granted in the future, calculated as $Ln\ (\Delta Grant_{it+3}+1)\ if\ \Delta Grant_{it+3} \geq 0, and\ -Ln(-\Delta Grant_{it+3}+1)\ if\ \Delta Grant_{it+3} < 0$. $\Delta Grant_{it+3}$ is calculated as $Grant_{it+3} - \frac{1}{2}(Grant_{it-1} + Grant_{it-2})$, where *Grant*$_{it}$ is the number of patent applications by firm *i* in year *t* that are eventually granted in the future.
LnΔCiteInd$_{it+3}$	The natural logarithm of the percentage change in the number of citations of industry peers' patents by firm *i*'s patent applications in year *t+3*, calculated as $Ln\ (\Delta CiteInd_{it+3}+1)\ if\ \Delta CiteInd_{it+3} \geq 0, and\ -Ln(-\Delta CiteInd_{it+3}+1)\ if\ \Delta CiteInd_{it+3} < 0$. $\Delta CiteInd_{it+3}$ is calculated as $\left[CiteInd_{it+3}/[\frac{1}{2}(CiteInd_{it-1} + CiteInd_{it-2})] - 1\right]$, where *CiteInd*$_{it}$ is the average number of citations of industry peers' patents by firm *i*'s patent applications in year *t*.

TABLE 1 Sample selection

	Number of site visits	Number of firm-years	Number of unique firms
Site visits during 2013–2019	47,310	9,172	2,331
After excluding firm-years with missing information on visitor identities	45,185	8,741	2,147
After excluding firm-years from the financial industry	45,126	8,722	2,139
After excluding firm-years with missing values for the variables used in the regression analyses	39,793	7,284	1,995

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

TABLE 2 Descriptive statistics

	N	Mean	Std.	Q1	Median	Q3
Dependent variable						
$\Delta R\&D_{it+1}$	7,284	3.103	5.642	0.022	1.393	4.087
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						
$InnoNews_{it}$ *(Raw value)*	7,284	10.323	12.457	2.444	6.236	13.840
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_{jt}	7,284	0.087	0.101	0.028	0.060	0.109
$KZindex_{it}$	7,284	1.312	2.048	0.104	1.477	2.689

Note: This table presents summary statistics. The sample includes 7,284 firm-years for the period of 2013–2019. See Appendix for variable definitions.

TABLE 3 Analysts' questions about innovation and future R&D investments

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$\boldsymbol{AnalystAsk_{it}}$	**0.378*** **	**0.946*** **
	(2.95)	**(4.39)**
$InnoNews_{it}$	0.241***	0.241***
	(2.79)	(2.81)
AC_{it}	0.463***	0.487***
	(5.13)	(5.39)
$Size_{it}$	0.123	0.134
	(1.00)	(1.10)
Age_{it}	−0.021	−0.020
	(−1.36)	(−1.30)
$Leverage_{it}$	3.144***	3.155***
	(4.27)	(4.28)
$Profit_{it}$	1.068***	1.046***
	(3.99)	(3.92)
BM_{it}	−2.430***	−2.412***
	(−5.67)	(−5.63)
$R\&D_{it}$	0.410***	0.404***
	(9.67)	(9.59)
$CASH_{it}$	−4.782***	−4.846***
	(−4.61)	(−4.68)
PPE_{it}	−3.551***	−3.503***
	(−6.10)	(−6.04)
$CAPEX_{it}$	4.347**	4.189**
	(2.29)	(2.21)
$InstOwn_{it}$	−0.014	−0.032
	(−0.04)	(−0.09)
HHI_{jt}	−1.549*	−1.489*
	(−1.89)	(−1.82)
$KZindex_{it}$	−0.569***	−0.574***
	(−6.75)	(−6.84)
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.288	0.290

Note: This table presents the regression results for the impact of financial analysts asking questions about innovation during site visits ($AnalystAsk_{it}$) on future R&D investments ($\Delta R\&D_{it+1}$). $AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. See Appendix for variable definitions. The *t*-values in parentheses 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.

TABLE 4 Analysts' questions about innovation and future R&D investments: using the initial coverage of innovation-expert analysts as a shock

Panel A: Validation test of the shock

Dependent variable =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
InnoExpert_Cover*it*	**0.109*** **	**0.043** **
	(3.98)	**(2.17)**
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.104	0.079

Panel B: The effect of the initial coverage of an innovation-expert analyst on future R&D investments

Dependent variable =	$\Delta R\&D_{it+1}$
	(1)
InnoExpert_Cover*it*	**1.066*** **
	(2.77)
Control variables	YES
Year, industry fixed effects	YES
Observations	7,284
Adj. R^2	0.288

Note: This table reports the results when using the initial coverage of innovation-expert analysts as a shock to examine the likelihood of analysts asking questions about innovation during site visits. Panel A reports the results of the impact of having an innovation-expert analyst starting to cover firm *i* in year *t* ($InnoExpert\_Cover_{it}$) on the likelihood of analysts asking questions about innovation during site visits ($AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$). Panel B reports the results of the impact of having an innovation-expert analyst starting to cover firm *i* in year *t* on the firm's future R&D investments. See Appendix for other variable definitions. The *t*-values in parentheses 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.

TABLE 5 Analysts' questions about innovation and future R&D investments: subsample with innovation-related words first appearing in analysts' questions

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$\boldsymbol{AnalystAsk_{it}}$	**0.383*** **	**1.001*** **
	(2.56)	**(3.67)**
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	5,574	5,574
Adj. R^2	0.271	0.273

Note: This table presents the regression results for the impact of financial analysts asking questions about innovation during site visits ($AnalystAsk_{it}$) on future R&D investments ($\Delta R\&D_{it+1}$) based on the subsample with innovation-related keywords appearing in analysts' questions first. $AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. $AnalystAsk\_D_{it}$ is an indicator variable for analysts asking questions about innovation, which is equal to one if there is at least one site visit with security analyst participants in which firm *i* is asked about innovation and innovation-related keywords appear in analysts' questions first in year *t*, and zero otherwise. $AnalystAsk\_R_{it}$ is the ratio variable for analysts asking questions about innovation and innovation-related keywords appearing in analysts' questions first, i.e., number of site visits with security analyst participants in which firm *i* is asked about innovation first, divided by the total number of site visits to firm *i* in year *t*. The sample for this analysis includes (1) 2,393 firm-years where innovation keywords appear in analysts' questions first for at least one site visit and (2) 3,181 firm-years without site visits containing innovation-related words in analysts' questions. See Appendix for other variable definitions. The *t*-values in parentheses 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.

TABLE 6 Analysts' questions about innovation and future R&D investments: controlling for firm Fixed Effects

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$	**0.287***	**0.516***
	(1.95)	**(1.83)**
Control variables	YES	YES
Year, firm fixed effects	YES	YES
Observations	2,935	2,935
Adj. R^2	0.581	0.581

Note: This table presents the regression results for the impact of financial analysts asking questions about innovation during site visits ($AnalystAsk_{it}$) on future R&D investments ($\Delta R\&D_{it+1}$) controlling for firm fixed effects. $AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. See Appendix for variable definitions. To increase the power of the tests, we restrict the sample to firms with at least six observations during the sample period. The *t*-values in parentheses 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.

TABLE 7 Analysts' questions about innovation and future R&D investments: cross-sectional analyses of the knowledge spillover effect

Panel A: Analyses based on the number of firms in the same industry covered by visiting analysts (*$IndCoverage_{it}$*)

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$ × $IndCoverage_{it}$	**0.493****	**0.723***
	(2.14)	**(1.93)**
$AnalystAsk_{it}$	0.154	0.497*
	(0.85)	(1.69)
$IndCoverage_{it}$	−0.801***	−0.727***
	(−3.88)	(−3.73)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.291	0.292

Panel B: Analyses based on firms' technological similarity with industry peers (*$TechSimilarity_{it}$*)

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$ × $TechSimilarity_{it}$	**0.298***	**0.122**
	(1.76)	**(0.32)**
$AnalystAsk_{it}$	0.249**	0.749***
	(2.41)	(2.84)
$TechSimilarity_{it}$	0.286*	0.207
	(1.93)	(1.05)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.342	0.291

TABLE 7 (Cont'd)

Panel C: Analyses based on the coverage of innovation-expert analysts (*InnoExpertAsk*$_{it}$)

Dependent variable =	$\Delta R\&D_{it+1}$	
AnalystAsk$_{it}$ =	*AnalystAsk_D*$_{it}$	*AnalystAsk_R*$_{it}$
	(1)	(2)
***AnalystAsk*$_{it}$ × *InnoExpertAsk*$_{it}$**	**0.527****	**0.917****
	(2.17)	**(2.20)**
AnalystAsk$_{it}$	0.295**	0.757***
	(2.22)	(3.31)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.289	0.291

Note: This table presents regression results for the impact of financial analysts asking questions about innovation during site visits (*AnalystAsk*$_{it}$) on future R&D investments ($\Delta R\&D_{it+1}$) conditional on the potential for knowledge spillovers across firms. *AnalystAsk*$_{it}$ is one of the following two variables: *AnalystAsk_D*$_{it}$ and *AnalystAsk_R*$_{it}$. The proxies for potential spillover effects are the number of firms in the same industry covered by visiting analysts (*IndCoverage*$_{it}$) in Panel A, the technological similarity between the focal firm and other firms in the industry (*TechSimilarity*$_{it}$) in Panel B, and having an innovation-expert analyst participating in site visits with questions on innovation (*InnoExpertAsk*$_{it}$) in Panel C. See Appendix for variable definitions. The *t*-values in parentheses 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.

TABLE 8 Analysts' questions about innovation and future R&D investments: tests of the information hypothesis

Panel A: Analyses based on analyst coverage (*AC_L_{it}*)

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it} \times AC\_L_{it}$	**−0.831*****	**−2.027*****
	(−3.49)	**(−4.85)**
$AnalystAsk_{it}$	0.828***	2.128***
	(4.57)	(6.04)
AC_L_{it}	0.196	0.294
	(0.80)	(1.29)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.290	0.294

Panel B: Analyses based on firm size (*$Size\_L_{it}$*)

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it} \times Size\_L_{it}$	**−0.562****	**−1.535*****
	(−2.30)	**(−3.73)**
$AnalystAsk_{it}$	0.651***	1.756***
	(3.79)	(5.52)
$Size\_L_{it}$	−0.038	0.096
	(−0.16)	(0.42)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.289	0.292

TABLE 8 (Cont'd)

Panel C: Analyses based on media coverage (*$NewsCov\_L_{it}$*)

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$ × $NewsCov\_L_{it}$	**−0.925*****	**−1.676*****
	(−3.83)	**(−3.98)**
$AnalystAsk_{it}$	0.869***	1.919***
	(4.47)	(5.11)
$NewsCov\_L_{it}$	−0.141	−0.199
	(−0.68)	(−1.05)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.292	0.295

Note: This table presents regression results for the impact of financial analysts asking questions about innovation during site visits ($AnalystAsk_{it}$) on future R&D investments ($\Delta R\&D_{it+1}$) conditional on the information environment of the firm. $AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. The proxies for firms' information environment quality are an indicator for low analyst coverage (AC_L_{it}) in Panel A, an indicator for low firm size ($Size\_L_{it}$) in Panel B, and an indicator for low media coverage ($NewsCov\_L_{it}$) in Panel C. See Appendix for variable definitions. The *t*-values in parentheses 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.

TABLE 9 Analysts' questions about innovation and future R&D investments: tests of the monitoring hypothesis

Panel A: Analyses based on large shareholders' ownership (*Own_L_{it}*)

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$ × Own_L_{it}	**−0.230**	**−0.495**
	(−0.93)	**(−1.22)**
$AnalystAsk_{it}$	0.506***	1.201***
	(2.64)	(3.81)
Own_L_{it}	−0.413**	−0.400**
	(−2.33)	(−2.48)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.290	0.292

Panel B: Analyses based on board meeting frequency (*$BoardMeet\_L_{it}$*)

Dependent variable =	$\Delta R\&D_{it+1}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$AnalystAsk_{it}$ × $BoardMeet\_L_{it}$	**−0.536****	**−0.504**
	(−2.22)	**(−1.26)**
$AnalystAsk_{it}$	0.664***	1.196***
	(3.34)	(3.89)
$BoardMeet\_L_{it}$	−0.539***	−0.690***
	(−3.14)	(−4.53)
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	7,284	7,284
Adj. R^2	0.294	0.295

Note: This table presents regression results for the impact of financial analysts asking questions about innovation during site visits ($AnalystAsk_{it}$) on future R&D investments ($\Delta R\&D_{it+1}$) conditional on firms' agency problems. $AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. The proxies for firms' agency problems are an indicator for low ownership of the second to the tenth largest shareholders (Own_L_{it}) in Panel A and an indicator for a low number of board meetings ($BoardMeet\_L_{it}$) in Panel B. See Appendix for variable definitions. The *t*-values in parentheses 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.

TABLE 10 Analysts' questions about innovation and future patent applications and citations

Panel A: Descriptive statistics on patent related variables

VARIABLES	N	Mean	Std.	Q1	Median	Q3
$\Delta Patent_{it+3}$	5,935	51.470	151.300	0.000	12.500	45.000
$Ln\Delta Patent_{it+3}$	5,935	1.867	2.722	0.000	2.603	3.829
$\Delta Grant_{it+3}$	5,935	31.760	98.320	−0.500	7.000	30.000
$Ln\Delta Grant_{it+3}$	5,935	1.438	2.643	−0.405	2.079	3.434
$\Delta CiteInd_{it+3}$	4,324	0.280	1.084	−0.341	0.138	0.647
$Ln\Delta CiteInd_{it+3}$	4,324	0.137	0.596	−0.294	0.129	0.499

Panel B: Analyses based on the quantity and quality of patent applications ($Ln\Delta Patent_{it+3}$, $Ln\Delta Grant_{it+3}$)

Dependent variable =	$Ln\Delta Patent_{it+3}$		$Ln\Delta Grant_{it+3}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)	(3)	(4)
$\boldsymbol{AnalystAsk_{it}}$	**0.218***	**0.201**	**0.218***	**0.196**
	(2.68)	**(1.60)**	**(2.80)**	**(1.60)**
Control variables	YES	YES	YES	YES
Year, industry fixed effects	YES	YES	YES	YES
Observations	5,935	5,935	5,935	5,935
Adj. R^2	0.080	0.079	0.060	0.059

Panel C: Analyses based on cross-citations of industry peers' patents ($Ln\Delta CiteInd_{it+3}$)

Dependent variable =	$Ln\Delta CiteInd_{it+3}$	
$AnalystAsk_{it}$ =	$AnalystAsk\_D_{it}$	$AnalystAsk\_R_{it}$
	(1)	(2)
$\boldsymbol{AnalystAsk_{it}}$	**0.036***	**0.030**
	(1.82)	**(1.02)**
Control variables	YES	YES
Year, industry fixed effects	YES	YES
Observations	4,324	4,324
Adj. R^2	0.063	0.063

Note: This table reports regression results from the patent analyses. Panel A reports the descriptive statistics on patent-related variables. Panels B and C present the regression results for the impact of financial analysts asking questions about innovation during site visits ($AnalystAsk_{it}$) on future patent applications ($Ln\Delta Patent_{it+3}$), future patent applications that are eventually granted ($Ln\Delta Grant_{it+3}$), and citations of industry peers' patents ($Ln\Delta CiteInd_{it+3}$). $AnalystAsk_{it}$ is one of the following two variables: $AnalystAsk\_D_{it}$ and $AnalystAsk\_R_{it}$. See Appendix for the definitions of other variables. The *t*-values in parentheses 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.