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Asymmetric Information and R&D Disclosure: Evidence from Scientific Publications

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Abstract. We examine how asymmetric information in financial markets affects voluntary research and development (R&D) disclosure, considering scientific publications as a disclosure channel. Difference-in-differences regressions around brokerage house mergers and closures, which increase information asymmetry through reductions in analyst coverage, indicate a quick and sustained increase in scientific publications from treated firms relative to the number of publications from control firms. The treatment effects are concentrated among firms with higher information asymmetry and lower investor demand, firms with greater financial constraints, and firms with lower proprietary costs. We do not find evidence of changes in financial disclosure, nor do we find changes in patenting. Results from ordinary least squares regressions show that scientific publications by firms are positively associated with investor attention toward those firms. We complement these results with qualitative evidence from conference calls. Our results highlight the limitations and tradeoffs R&D firms face in their financial market disclosure policies.

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Keywords: financial analysts • information asymmetry • investor attention • R&D disclosure • scientific publications

1. Introduction

The consequences of information asymmetry in financial markets are a long-standing concern in accounting and finance research (Merton 1987, Diamond and Verrecchia 1991). A central theme of these studies is that information asymmetry can lead to an increase in the cost of capital or even an inability to attract external capital.[1] There is considerable evidence that firms can reduce information asymmetry by providing voluntary disclosure, such as management forecasts or 10-K filings (Francis et al. 2008, Balakrishnan et al. 2014). However, the relation between information asymmetry and voluntary disclosure is less clear for research and development (R&D) firms because capital market benefits can be offset by information leakage to rivals (Bhattacharya and Ritter 1983).

Aboody and Lev (2001) emphasize important differences between R&D and other investments in terms of information asymmetry. First, R&D is firm-specific, which makes it difficult for investors to infer the productivity and value of a firm's R&D by observing the R&D performance of other firms. Second, R&D is not traded in organized markets from which investors can obtain information on R&D investments' productivity and value. Finally, accounting principles require R&D to be immediately expensed and do not require financial reporting on the productivity or value of R&D investments. Hence, there should be substantial demand from financial markets for firms to disclose information about their R&D activities (Deng et al. 1999).

In this paper, we analyze the relation between information asymmetry and voluntary R&D disclosure and focus on a type of R&D disclosure that has received surprisingly little attention in the academic literature: publications in academic journals. Why should investors care about corporate publications in academic journals? A substantial proportion of firms' R&D outputs are published in academic journals, and large, R&D-intensive companies, such as Google, IBM, and Merck, are included in the prestigious Nature Index.[2] Scientific publications provide information not only on R&D productivity, but also on firms' R&D capabilities thanks to the thorough peer-review process and well-known journal rankings (Dasgupta and David 1994). Moreover, it is typically basic research that is disclosed in the form of scientific publications (Arora et al. 2021), and the contribution of basic research to firm productivity is larger than that of other types of R&D (Czarnitzki and Thorwarth 2012).

However, whether firms use scientific publications to communicate with investors is an open question. Some anecdotal evidence emerged in a recent policy workshop.[3] Jochen Maas, managing director at Sanofi-Aventis Germany, suggests that firms use scientific publications to certify and enhance their reputation, generate interest among investors, and stimulate share prices. In addition, he points out that, compared with patents, publications are a much faster and cost-effective way to build awareness among investors.[4] There is also evidence that the decision to publish scientific papers is strategic. A number of case studies conclude that what most deters firms from publishing is the risk of knowledge leakage to rivals (Polidoro and Theeke 2012).

We draw from the literature exploring the causal effects of information asymmetry on various firm and capital market outcomes to provide evidence that firms seek to communicate with investors through scientific publications and that such efforts have implications for the cost of capital. Specifically, our empirical tests exploit brokerage house mergers and closures that generate plausibly exogenous reductions in analyst coverage. This approach was first advocated by Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012), who document that such declines cause an increase in information asymmetry, a decrease in a firm's share price, and a reduction in investors' demand for a stock.

Our empirical approach uses 43 brokerage house mergers and closure events staggered over time from 2000 until 2010 and considers publicly traded U.S. firms that are active in R&D. Associated with these events are 760 firms that were covered in the year before the event by both merging houses or the closing house, our treatment sample. Using a difference-in-differences (DiD) approach, we compare changes in the scientific publication rates of this treatment sample to those of a control sample of firms unaffected by the brokerage house merger/closure, thus identifying the causal change in scientific publication rates from the loss of coverage.

We find that firms experiencing a decline in analyst coverage adjust scientific disclosures; namely, their publication rates increase. The increase is statistically significant and economically meaningful: our baseline analysis indicates an increase of 10.5%–12.6% in the number of publications because of coverage shocks. We limit concerns regarding systematic differences across firms, years, or events by including the respective fixed effects. We also account for differences in observable characteristics by including control variables. Our results are robust to using a matching estimator. We examine the dynamic effects of broker mergers/closures and show that we do not violate the parallel trends assumption. Publication rates for the treatment sample increase mainly between the year before and the year after the shock, corroborating the interpretation that firms increase their scientific publications in an attempt to communicate with investors. This is further supported by qualitative evidence from conference calls.

The identified treatment effects are concentrated in the following subsamples: firms with higher information asymmetry and lower investor demand, firms with greater financial constraints, and firms with lower proprietary costs. For instance, scientific publications from firms that are financially constrained increase by up to 23.5%, whereas the corresponding effect is insignificant for firms that are financially unconstrained. Similarly, we find that scientific publications from firms with low proprietary costs increase by up to 23.0%. Among the set of firms with high proprietary costs, the effect is economically small and statistically insignificant. This is consistent with the existence of a trade-off between capital market benefits from increased R&D disclosure and the risk associated with revealing proprietary information to rivals (Bhattacharya and Ritter 1983).

Next, we consider three alternative perspectives. First, firms may simply communicate with investors through financial disclosures (Balakrishnan et al. 2014). However, the DiD tests do not show a significant change in managerial earnings forecast provision behavior in the treatment sample. Second, we explore the alternative interpretation that analysts impose short-term pressure on managers and reductions in coverage encourage them to increase R&D investments (He and Tian 2013). We observe no evidence of changes in R&D expenses, patenting, or the use of scientific research in patents. Nor do we see meaningful changes in the incidence of hiring scientists. Third, analysts may monitor managers (Chen et al. 2015). However, we see no evidence of changes in firms' fundamental performances. In addition, the effect of the coverage shocks on scientific publications is not observed among firms with poor governance, which is also inconsistent with a monitoring explanation for our results.

Finally, we examine whether scientific publications influence investors' attention and financial markets. Merton (1987) describes a channel whereby increased investor attention is associated with a decrease in the cost of capital and an increase in share prices. We use three empirical proxies in ordinary least squares (OLS) regressions to analyze the relation between scientific publications and investor attention at the firm–month level. We find that scientific publications are associated with increased news articles, Google searches for company tickers, and news-searching activity on Bloomberg terminals after we include firm–year fixed effects, month fixed effects, and controls for other stock characteristics related to investor attention.

Our paper contributes to the literature on voluntary disclosure and firms' response to asymmetric information in financial markets by documenting the relation between asymmetric information and the voluntary disclosure of scientific research. In particular, we extend the traditional research on voluntary disclosure beyond the narrow focus on financial disclosure, which is short-term oriented (Francis et al. 2008, Balakrishnan et al. 2014). In contrast, scientific disclosure, which is broad in scope, is related to a firm's long-term performance and growth opportunities. Our focus on scientific disclosure answers the call of Leuz and Wysocki (2016) for more research on nontraditional disclosure, and our results provide evidence on the limitations and trade-offs firms face in their financial market disclosure practices.

We also contribute to the growing literature on R&D disclosure, which focuses on the disclosure of downstream inventions and provides evidence on the consequences of R&D disclosure (Kim and Valentine 2021, Martens 2021). In contrast, we focus on the disclosure of upstream research and on understanding the determinants of voluntary R&D disclosure choices. Our results provide evidence on whether and under what conditions firms use voluntary R&D disclosure as an important conduit of communication with investors in response to adverse shocks to information asymmetry. In addition, our results provide novel evidence on the consequences of voluntary R&D disclosure by documenting the relation between the voluntary disclosure of scientific research and investor attention.

2. Theoretical Development and Related Literature

2.1. Asymmetric Information and Scientific Publications

Information asymmetries among investors create trading frictions by inducing adverse selection, which leads to lower liquidity. This illiquidity is priced by the market, increasing a firm's cost of capital. Theoretical models propose that a firm's commitment to greater disclosure can reduce information asymmetry and lower the cost of capital. For instance, Diamond (1985) shows that disclosure reduces the costs of private information acquisition by some investors; Lambert et al. (2007) show that higher quality firm-specific disclosures decrease the covariance of a firm's cash flow with the cash flows of other firms; and Merton (1987) shows that greater disclosure increases investors' awareness of a firm's existence and enlarges its investor base, which improves risk sharing and reduces the cost of capital.

These mechanisms likely apply to both financial and R&D disclosure as long as the information concerned is value-relevant. Indeed, a fair amount of research suggests that scientific publications are value-relevant (Simeth and Cincera 2016, Hsu et al. 2021). Of course, scientific publications can affect a firm's financial performance and value through channels other than those related to financial disclosure. For instance, some scientific publications may reduce information asymmetries by assisting investors in evaluating the characteristics of a firm's current and future sales revenues (Azoulay 2002).

Scientific publications may also enhance capital market participants' perceptions of the firm; that is, firms may benefit from a positive association between academic recognition and firm capabilities (Audretsch and Stephan 1996). When firms publish in academic journals, the scientific community certifies that the research is consistent with academic standards. Scientific publications also convey positive signals about the quality of the firm's R&D activities. It is, therefore, not uncommon for R&D-active firms to report scientific publications in their earnings conference calls when discussing the firm's accomplishments (Section 3).

Firms choosing to publish scientific articles may also benefit from increased investor attention. Studies find that increased investor attention to information events is associated with improvements in liquidity (Grullon et al. 2004). Furthermore, firms often manage investor attention strategically through, for instance, the timing of the disclosure (deHaan et al. 2015). In the R&D context, Fitzgerald et al. (2021) propose that investors pay little attention to incremental R&D. However, the authors also propose the opposite for explorative R&D; because individuals tend to place higher emphasis on novel and unique signals, investors devote more time to understanding the economic significance of ideas unfamiliar to them.

Following this logic, there are several arguments for why scientific publications may be effective in attracting investor attention. First, the nature of scientific inquiry involves discovering new cause–effect relationships, and novelty is an important criterion in the peer-review process (Dasgupta and David 1994). This creates significant barriers to publication in scientific journals, which, in turn, reduce the amount of information to be processed. Second, scientific quality is readily observable at the moment of publication thanks to well-established journal rankings, making it easier for investors to compare R&D outputs across firms. Third, the media play a relevant role in the dissemination of scientific articles because the popular press frequently covers exciting research findings.

Having established the benefits of scientific publications, we now move to the counterpart of such benefits in the disclosure trade-off: proprietary costs. Early theoretical models argue that managers follow a full-disclosure policy because, in the absence of disclosure, investors assume the worst regarding the firm's prospects and discount the value of the firm (Grossman 1981). However, the existence of proprietary information extends the range of possible explanations for why managers withhold information: managers disclose proprietary information only when the increase in firm value from disclosure exceeds the associated proprietary costs (Verrecchia 1983).

Entwistle (1999) interviewed senior executives of leading technology firms in Canada, and most interviewees reported being "very concerned" about revealing proprietary R&D information. In terms of scientific publishing, revealing information about the firm's latest discoveries, at a minimum, provides useful information to rivals about the firm's research direction. At the maximum, it can facilitate rivals' attempts to imitate technologies, refine existing products, or make subsequent discoveries (Polidoro and Theeke 2012).

To protect themselves against competitive damages, most firms approach scientific publications strategically. Based on survey responses from executives at life science firms, Blumenthal et al. (1996) document publication restrictions in the context of collaborative research with academic partners. For instance, 58% of the respondents stated that their firm requires scientists to keep information confidential. Using survey responses from firms engaged in university licensing, Thursby and Thursby (2007) report that 90% of the contracts included publication delay clauses. Taking a different perspective, Czarnitzki et al. (2014) asked academic scientists about any disclosure restrictions they experienced in research funded by industry. Of the respondents with industry sponsorship, 41% reported partial or full secrecy requirements on publications.

In sum, the costs associated with releasing publications include the fact that the information can help rivals that would use the information to the firm's disadvantage, whereas the benefits can include reduced information asymmetry regarding current and expected sales revenues; positive exposure via association with strong scientific capabilities; and in response to visibility concerns, an increased capacity to attract attention from market participants. We hypothesize that a shift in the relative benefits of scientific publications because of shocks to information asymmetries increases the likelihood of firms choosing to publish scientific articles instead of keeping the information secret.

Although we focus on scientific publications, we acknowledge that firms may also choose alternative R&D disclosure strategies in response to adverse shocks to information asymmetry. Perhaps the most important alternative is patenting. In contrast to scientific publications, patents disclose inventions and also grant the right to exclude others from using those inventions. In addition, applicants can obfuscate the textual content in patents (Roin 2005), which may reduce disclosure costs. Notwithstanding these advantages, it turns out that managers do not necessarily prefer patenting (Section 1). This is because the information is disclosed with substantial delay: patent applications are only disclosed 18 months after filing, and it can take several years for the patent office to certify that the invention in question is worth a patent. In addition, it is difficult for investors to discern quality differences among new patents because measures such as patent citations take time to accumulate. Therefore, patenting should be less effective in settings such as ours because they require a timely response.[5]

Firms may choose other channels, such as press releases, to communicate research findings to investors. However, such sources alone are unlikely to provide investors with sufficient information to assess firms' scientific performance. Detailed scientific disclosure has the potential to provide the additional information necessary for investors to assimilate these summary disclosures. In addition, scientific publications are peer-reviewed and, hence, provide certification for a firm's claims regarding its research performance. Finally, managers have expressed concerns over disclosing detailed information about research findings through other channels because doing so might prevent them from publishing in academic journals (Section 3). Therefore, scientific publications can provide more value-relevant information to investors than other sources.

2.2. Related Studies on Financial Analysts

We examine the effects of asymmetric information shocks among financial analysts. A large body of literature argues that analysts produce information that matters to market participants. Extensive evidence documents the beneficial and informative role played by analysts (Hong et al. 2000, Barth and Hutton 2004). The literature also finds that analysts' reports impact stock prices by increasing investor awareness and demand for stocks (Womack 1996). By producing information about the firms they cover, analysts also monitor these firms (Chen et al. 2015).

There are some discrepancies in the literature with respect to the relation between analyst coverage and R&D activities. Barth et al. (2001) argue that analysts have more incentives to follow R&D-intensive firms than firms with lower or no R&D. This is the case because following firms with more R&D can yield more profitable investment recommendations and higher trading commissions. In addition, analysts expend greater effort to follow such firms. In contrast, He and Tian (2013) characterize analysts in a negative light, arguing that analysts impose short-term pressure on managers, exacerbate managerial myopia, and impede R&D. The authors show that firms with higher analyst coverage have lower R&D outputs.

However, this inference is questioned by Clarke et al. (2015), who show that the negative relation between analyst coverage and patenting demonstrated by He and Tian (2013) is driven by firms with either zero patents or zero citations in the past, that is, firms with little R&D. For firms with substantial R&D, this relation turns positive. The authors conclude that the informational role is predominant for R&D firms. There is also evidence from analysts' reports on this matter. Bellstam et al. (2021) propose a new measure of corporate R&D derived from textual descriptions of firm activities in analysts' reports and find that this measure correlates strongly with patenting and R&D intensity among patenting firms.

Our study differs from He and Tian (2013) in three important aspects. First, instead of including non-R&D firms, we restrict attention to R&D firms. Second, instead of focusing on patenting, we focus on scientific publishing. Third, instead of interpreting scientific publications as a measure for R&D investment, we interpret the relation between publication rates and coverage as evidence that firms change their level of scientific disclosure in response to changes in the number of analysts following them. Notably, our paper is not the first to see communication possibilities in the relation between analyst coverage and R&D outcomes. Reeb and Zhao (2020, p. 157) remark that "financial intermediaries potentially influence the disclosure of innovation rather than research and development success."

Our study is also related to Balakrishnan et al. (2014). The authors show that an increase in information asymmetry stemming from brokerage house mergers and closures leads to an increase in firms' voluntary disclosure. Similarly to our work, Balakrishnan et al. (2014) also maintain that firms that increase their disclosures exhibit an increase in the liquidity of their shares. However, in contrast to our study, Balakrishnan et al. (2014) focus on financial disclosure in the form of earnings guidance regarding earnings per share (EPS) numbers. Prior studies emphasize that financial disclosures are largely irrelevant for security valuation for R&D-intensive firms (Amir and Lev 1996, Palmon and Yezegel 2012). In contrast, we focus on the disclosure of R&D outcomes, motivating us to use scientific publications as a means of disclosure.

2.3. Related Studies on R&D Disclosure

Previous studies examine the relation between capital markets and forms of R&D disclosure other than scientific publications. For instance, Guo et al. (2004) examine product-related disclosures in the prospectuses of biotech firms conducting initial public offerings and document a negative relation between extent of disclosure and the bid–ask spread. Cao et al. (2018) examine product development–related press releases and find positive return reactions to product disclosure. Merkley (2014) examines R&D-related sentences in 10-Ks and finds a negative relation between the extent of disclosure and the bid–ask spread. In a recent paper, Kim and Valentine (2023) find that R&D-related sentences in 10-Ks are associated with an increase in patent sales.

Prior studies also examine the relation between capital markets and R&D disclosure in the context of patents. For instance, Dass et al. (2020) examine increases in patenting following the enactment of stronger legal protection of patents and find reductions in the bid–ask spread and leverage. Martens (2021) finds that easier access to patent information following openings of patent libraries across U.S. counties increases the trading volume of local retail investors. Saidi and Žaldokas (2021) show that an increase in patent disclosure following a change in patent law that requires the patent office to publish patent applications 18 months after filing helps firms switch lenders, resulting in a lower cost of debt.

Although the literature also supports the notion that increased disclosure is related to higher patenting rates (Brown and Martinsson 2019), consistent with the benefits of reducing information asymmetry, the evidence on the relation between R&D disclosure and proprietary costs is somewhat mixed. For instance, consistent with the view that revealing information through patent applications can impose proprietary costs, Kim and Valentine (2021) find that a mandated increase in patent disclosure increases firm patenting rates when rivals reveal more information and decreases firm patenting rates when rivals obtain more information. However, in their study of patent applications, Glaeser and Landsman (2021) conclude that firms use patent disclosure to deter competitors.

In contrast to this literature, the present paper focuses on scientific publications. Scientific publications represent basic research, which is the output that marks the beginning of the R&D process. In contrast, patents represent inventions, which are obtained in the later stages of the R&D process. This distinction is important because upstream scientific research is a more potent source of knowledge spillovers to rivals than are downstream inventions (Arora et al. 2021). There is also evidence that there is more demand for information about the former from investors (Pinches et al. 1996). Although anecdotal, Deng et al. (1999) note that firms tend not to disclose information about scientific research in their financial statements, but do share information about applied research or process R&D.

Patents and scientific publications may also overlap if individual research activities contribute to both scientific research and downstream inventions. However, data on scientists who engage in both research and the development of inventions suggest a rather loose integration between research and invention activities at the firm level (Sheer 2022). Moreover, evidence on citation patterns in patent–paper pairs indicates that scientific publications contain information beyond that contained in patents. Indeed, Magerman et al. (2015) find no evidence for a relative decrease in forward citations to publications for which a patent document has been identified during the period both before and after the granting of a patent.

3. Evidence from Conference Calls

Before turning to our systematic analysis, we provide evidence of the relevance of scientific publishing for R&D firms by looking at conference call discussions between senior management and investors that took place during periods when the firm was facing difficulties raising external funds and investors were concerned about the firm's share price. We quote from an August 2008 earnings call of one of the firms included in our sample, Aastrom Biosciences:

> [Question] Now can you answer a question sort of going back to the share price? And this goes back to promoting the company. Can you tell me why are you guys not promoting the company more regarding share price … ? Why is Aastrom so quiet about this? Why not tell the world "Hey, we are doing this," and try to attract new investors and new money into the company? Considering that you have made cardiac the focus of Aastrom, wouldn't it make sense to do this? It seems like Aastrom was extremely quiet throughout this period. And it really needs to be said that Aastrom needs to go the other direction. You need to get out there and promote this. You are telling us that everything is working, and we believe you. But if you don't get the message out to the world, you are not going to attract new investors.
>
> —Scott Smith (investor)

> [Answer] I think all I can say to put this in context is that we do not withhold any data that we have that we believe is relevant and meaningful. … What really carries the day, and what is important, is meaningful clinical data with statistically relevant numbers behind it. … We are trying to build a strong foundation of meaningful value with very solid clinical data that will stand up not only to regulatory, but peer review for publications by journals and in academic publications. That is really the only way that this is going to gain traction. And, in particular, the type of investors that we are interested in attracting.
>
> —George Dunbar (CEO), Aastrom Biosciences, 2008:Q4 Earnings Call, accessed from Thomson One.

As evidenced by these quotes, scientific publications can be a powerful means of attracting investor attention and financing. In the Online Appendix, Section A.1, we provide quotes on the other benefits of scientific publishing. We also provide quotes on managerial preferences for scientific publishing. Managers frequently emphasize that they are cautious about revealing too much information through alternative channels prior to journal publication because doing so could compromise the peer-review process and preclude them from publishing. As one manager commented, "We don't believe in science by press release; we believe in science by peer-reviewed journal publications. And so we really can't go too much into the data we're seeing right now."

4. Empirical Setup and Data

4.1. Identification Strategy

The most straightforward way to examine how information asymmetry in financial markets affects firms' scientific publication behavior is to regress scientific publications on the number of analysts following a firm. However, the estimates from such regressions are difficult to interpret because of endogeneity. For instance, if a positive relation between analyst coverage and scientific publications were uncovered, this could reflect the fact that analysts are attracted to firms that provide enhanced disclosure. Indeed, as we show in the Online Appendix, Section A.3, the relation between coverage and scientific publications (in a full panel) is positive and significant.

To overcome this problem, we consider a setting in which there is an unexpected shock to the number of analysts. Specifically, we use brokerage house mergers and closures as a source of plausibly exogenous variation in firms' analyst coverage (Hong and Kacperczyk 2010, Kelly and Ljungqvist 2012). We focus on broker disappearances between 2000 and 2010 and examine the effect of shocks to analyst coverage for the treated firms over the three fiscal years before $[-3, -1]$ and the three years after $[+1, +3]$ the brokerage merger/closure date. Our treatment sample is a combination of firms affected by brokerage merger/closure events from Kelly and Ljungqvist (2012), who cover the period between 2000 and 2008, and firms affected by events from Fich et al. (2018), who provide data on brokerage closures and mergers that occurred after 2008.

To identify firms whose coverage levels are affected by merger/closure events, we follow the approach put forth in He and Tian (2013) and Billett et al. (2017). First, for each event, we define the event period as the six months around the month of broker disappearance. Next, we retrieve all the firms covered by the brokers involved in the event in the 12 months before the event period $[-15, -3)$ and the analysts working for them. We assume that an analyst covers a firm if there is at least one earnings estimate in the Institutional Brokers' Estimate System (I/B/E/S) Detail History file for that firm in the pre-event period. Similarly, we assume that an analyst disappears if there is no earnings estimate from the analyst in the I/B/E/S records in the 12 months after the event period $(+3, +15]$.

For brokerage closures, we retain firms for which the analyst disappears from I/B/E/S in the postevent period; using those analysts who issue no earnings estimates during this period ensures that analysts who transition to other brokerage houses do not continue to cover these firms. For brokerage mergers, we retain firms covered by both the acquirer and the target broker before the merger period and for which one of their analysts disappears; this ensures that the resulting loss in coverage is indeed because of the brokerage merger. Furthermore, we exclude from the sample those firms that are no longer covered by the acquirer in the period after the event; the reason for this restriction is that such terminations could be endogenous because the acquiring broker has chosen to stop covering the firm for unobserved reasons.

Our treatment sample comprises 760 firms corresponding to 43 broker disappearances between 2000 and 2010.[6] To address the possibility that time series effects explain our results, we implement our identification strategy using a DiD methodology. This allows us to contrast the changes in the variables of interest for treated firms before and after the shock with the changes in the variables of interest for the control firms. In our setting, the control firms are all stocks that have analysts following in the pre-event period but that are not covered by the two merging brokers or the closing broker.

One remaining concern is that the treated and control firms differ in terms of observable dimensions, which may affect the estimate on the coverage loss. For instance, our estimate might be driven by larger firms being covered by more brokers (and, therefore, being more likely to be treated) and also having higher scientific publication rates. It is, thus, important to control for such systematic differences in our empirical specification to further isolate the effect of the coverage shock. Following Irani and Oesch (2013), we address this potential concern using two approaches. First, our basic approach is to incorporate firm fixed effects and control variables into the DiD regression framework. Second, we implement a DiD matching estimator.

4.2. Sample Construction

Our sample includes U.S. public firms for the period between 1997 and 2014.[7] We collect scientific publication information from Elsevier's Scopus database and analyst data from the I/B/E/S database. To calculate the control variables and the variables used in additional specifications, we add balance sheet data from Compustat and stock price data from the Center for Research in Security Prices (CRSP) database, institutional ownership data from Thomson's 13F database, text-based financial constraint measures from Hoberg and Maksimovic (2015), and patent data from Stoffman et al. (2022), among other data sources.

When constructing the sample of firm–year observations, we restrict the sample to observations with nonmissing (and positive values of) assets (item #6), sales (#12), and equity (#60) in the Compustat file. We eliminate financial and utility firms (firms with Standard Industrial Classification codes 4900–4999 and 6000–6999) and firms not headquartered in the United States based on their current headquarters location (*LOC*). We focus on firms that are active in R&D rather than sampling the entire Compustat universe. Because there is no consensus on what defines R&D firms, we follow the recent literature on scientific publications (Arora et al. 2021), which requires firms to have at least one patent and at least one year of positive R&D spending during the sample period.

4.3. Scientific Publications

We obtain scientific publication data from Scopus, which contains detailed records on peer-reviewed journals, trade publications, book series, and conference proceedings.[8] Each publication includes information on the publication title, journal title, and authors as well as an affiliation field with the name and address of the publishing institute or the firm. We focus on "articles" and "conference proceedings" from the list of document types as the most relevant outlets for novel scientific results. To identify firms' scientific publications, we standardize the names in the affiliation field and match these names to all the historical company names from the sample of CRSP/Compustat Merged Database firms.[9]

The main corporate publication variable used in this paper is the firm's total number of scientific publications in a given year. We set the publication count to zero for firms without available publication information in the Scopus database and then use the natural logarithm of the publication count as the main publication measure in our analysis (*LN_PUB*). To avoid losing firm–year observations with zero publications, we add one to the actual values when we calculate the natural logarithm. Because we are interested in the decision to disclose scientific research and because the average delays from submission to publication in natural science, engineering, and biomedical research tend to be less than one year, our preferred specification relates the coverage shock in the current year to scientific publications over the same period.

4.4. Control Variables

Our empirical setup enables us to add control variables. Incorporating these variables into our analysis mitigates concerns that observable differences between treated and control firms drive the estimates. When selecting control variables, we follow prior studies on the relation between analyst coverage and R&D outcomes that have developed a standard vector of firm and industry characteristics (He and Tian 2013, Guo et al. 2019).

These variables are firm size, *LN_AT*, measured by the natural logarithm of total assets; investment in R&D, *RDTA*, measured by R&D expenditures scaled by total assets; firm age, *LN_AGE*, measured by the natural logarithm of the number of years the firm is listed on CRSP/Compustat; asset tangibility, *PPETA*, measured by net property, plant, and equipment scaled by total assets; investment in fixed assets, *CAPEXTA*, measured by capital expenditures scaled by total assets; profitability, *ROA*, measured by return on assets; leverage, *LEV*, measured by total debt to total assets; growth opportunities, *Q*, measured by Tobin's Q; financial constraints, *DELAYCON*, measured by the Hoberg and Maksimovic (2015) text-based index; institutional ownership, *INSTOWN*, measured by the fraction of institutional investors; product market competition, *HINDEX*, measured by the Herfindahl index based on sales; and $HINDEX^2$, the squared Herfindahl index.

Summary statistics for these variables for both the treatment and control samples are presented in Table 1. The Online Appendix, Section A.2, defines the variables used in this study and lists their sources.

4.5. Model Specification

As discussed, we implement our quasi-experiment using a DiD methodology. Specifically, we follow Irani and Oesch (2013) and Guo et al. (2019) in estimating the following model:

$$Y_{i,e,t} = \alpha + \beta_1 Post_{e,t} + \beta_2 Treated_{i,e} + \beta_3 Post_{e,t} \times Treated_{i,e} + \gamma Z_{i,t} + \delta_t + \lambda_i + \theta_e + \varepsilon_{i,e,t}, \tag{1}$$

where i indexes the firm, e indexes the merger/closure event, t indexes the time, and $Y_{i,e,t}$ is the dependent variable, which is *LN_PUB* in our main specification. The variable $Post_{e,t}$ is a dummy equal to one if a firm–year observation is in the postevent period for event e, and $Treated_{i,e}$ is a dummy equal to one if firm i is part of the treatment sample for that event. The DiD coefficient is represented by β_3, which captures the impact of coverage terminations on changes in scientific publications for the treated firms relative to the publications of control firms. The variables δ_t, λ_i, and θ_e correspond to year, firm, and merger/closure event fixed effects that account for time-invariant unobservable factors particular to a year, a firm, or a specific merger/closure event that may influence scientific publication behavior across units.[10] $Z_{i,t}$ is the set of control variables presented. We cluster standard errors at the firm level.

5. The Effect of Coverage Shocks on Scientific Publications

5.1. Baseline Effect

We start with the key idea of the experiment: on average, treated firms should lose one analyst relative to control firms. We test this by estimating Equation (1) with the dependent variable replaced by analyst coverage (*COV*) and without including control variables. Given our experimental setup, we should observe a DiD coefficient close to minus one. Column (1) of Table 2 shows that this is indeed the case: the DiD coefficient is −1.045 and is significant at the 1% level. This result is consistent with related studies that utilize a similar research design.

Given this reduction in analyst coverage for the treatment sample, we also assess whether we observe an increase in information asymmetry in our data. The typical proxy used in the related literature is bid–ask spreads (Kelly and Ljungqvist 2012, Balakrishnan et al. 2014). We report the results in column (2). The estimated DiD coefficient in the spreads equation (*BASPRD*) is 0.278 and is

Table 1. Pre-event Characteristics for Treatment and Control Sample

	Panel A: Treatment sample						Panel B: Control sample					
Variable	Mean	25%	50%	75%	SD	*N*	Mean	25%	50%	75%	SD	*N*
LN_PUB	2.636	1.099	2.485	4.127	1.882	760	1.158	0.000	0.693	1.946	1.350	21,879
LN_AT	8.012	6.767	8.018	9.365	1.787	760	5.499	4.415	5.403	6.540	1.515	21,879
RDTA	0.074	0.018	0.057	0.107	0.074	760	0.093	0.017	0.053	0.122	0.121	21,879
LN_AGE	2.778	2.197	2.833	3.584	0.803	760	2.510	1.946	2.485	3.135	0.750	21,879
PPETA	0.204	0.085	0.160	0.270	0.157	760	0.187	0.076	0.150	0.262	0.142	21,879
CAPEXTA	0.048	0.022	0.037	0.063	0.035	760	0.043	0.018	0.032	0.054	0.038	21,879
ROA	0.125	0.085	0.135	0.195	0.129	760	0.052	0.008	0.104	0.163	0.204	21,879
LEV	0.165	0.013	0.143	0.269	0.153	760	0.141	0.000	0.089	0.244	0.155	21,879
Q	2.953	1.548	2.246	3.560	2.106	760	2.427	1.261	1.776	2.835	1.908	21,879
DELAYCON	−0.013	−0.064	0.000	0.009	0.073	760	−0.013	−0.080	−0.006	0.032	0.092	21,879
HINDEX	0.218	0.083	0.161	0.279	0.177	760	0.246	0.116	0.189	0.315	0.188	21,879
$HINDEX^2$	0.079	0.007	0.026	0.078	0.142	760	0.096	0.014	0.036	0.099	0.159	21,879
INSTOWN	0.685	0.566	0.708	0.823	0.178	760	0.544	0.342	0.569	0.755	0.256	21,879
COV	16.411	9.833	16.583	22.000	8.156	760	4.347	1.750	3.417	5.846	3.580	21,879
BASPRD	0.551	0.069	0.156	0.842	0.782	736	1.125	0.207	0.603	1.578	1.367	20,376

Notes. This table presents summary statistics for the treatment and control sample. Panel A reports summary statistics for the treatment sample. Panel B reports summary statistics for the control sample. The treatment sample is a combination of the brokerage merger and closure events from Kelly and Ljungqvist (2012) and Fich et al. (2018). Our sample includes 43 broker disappearances from 2000 to 2010. We follow the procedure put forth in He and Tian (2013) and Billett et al. (2017) to identify firms whose analyst coverage is reduced because of merger/closure events. The control sample is the remainder of firms in the CRSP/Compustat-merged universe with the required data and not covered by either the merging or closing brokers before the event. Variable definitions are provided in the Online Appendix, Section A.2.

Table 2. Regressions of Corporate Publications on Analyst Coverage Shocks

Dependent variable	*COV* (1)	*BASPRD* (2)	*LN_PUB* (3)	*IHS_PUB* (4)	*COV* (5)	*BASPRD* (6)	*LN_PUB* (7)	*IHS_PUB* (8)
TREATED × *POST*	−1.045***	0.278***	0.119***	0.146***	−1.007***	0.201***	0.100***	0.124***
	(0.231)	(0.038)	(0.031)	(0.036)	(0.213)	(0.035)	(0.030)	(0.035)
POST	−0.167***	0.053***	0.005	0.006	−0.077**	0.004	0.011	0.014
	(0.042)	(0.018)	(0.009)	(0.011)	(0.036)	(0.017)	(0.009)	(0.011)
TREATED	2.445***	−0.319***	−0.033	−0.052	2.071***	−0.151***	−0.042	−0.063
	(0.303)	(0.059)	(0.041)	(0.048)	(0.256)	(0.054)	(0.038)	(0.045)
LN_AT					2.292***	−0.553***	0.209***	0.250***
					(0.114)	(0.042)	(0.024)	(0.029)
RDTA					3.649***	−0.388	0.572***	0.718***
					(0.524)	(0.310)	(0.119)	(0.145)
LN_AGE					−0.294	0.026	−0.080	−0.095
					(0.219)	(0.085)	(0.053)	(0.064)
PPETA					1.145*	0.847***	0.168	0.183
					(0.642)	(0.207)	(0.146)	(0.181)
CAPEXTA					3.742***	−2.569***	0.157	0.212
					(1.126)	(0.453)	(0.258)	(0.319)
ROA					0.023	−0.835***	−0.049	−0.053
					(0.258)	(0.149)	(0.064)	(0.079)
LEV					−0.804**	0.848***	0.033	0.033
					(0.397)	(0.140)	(0.088)	(0.109)
Q					0.115***	−0.122***	−0.008	−0.010
					(0.023)	(0.011)	(0.006)	(0.007)
DELAYCON					0.950**	0.157	0.061	0.068
					(0.459)	(0.186)	(0.117)	(0.145)
HINDEX					0.039	−0.699	−0.529*	−0.671*
					(1.403)	(0.499)	(0.320)	(0.395)
HINDEX^2					−0.432	0.062	0.624**	0.810**
					(1.212)	(0.506)	(0.294)	(0.364)
INSTOWN					2.812***	−0.729***	−0.045	−0.045
					(0.309)	(0.113)	(0.072)	(0.088)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	122,429	114,536	122,429	122,429	122,429	114,536	122,429	122,429
Adjusted R^2	0.794	0.638	0.898	0.889	0.841	0.708	0.900	0.892

Notes. This table presents the baseline DiD results from the regression of corporate scientific publications on analyst coverage shocks. Robust standard errors are clustered by firm (in parentheses). The sample includes the treated and control firms assembled through the sample construction procedure described in Section 4.1. Variable definitions are provided in the Online Appendix, Section A.2.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

statistically significant at the 1% level. Hence, information asymmetry increases following coverage termination.

Next, we examine how this increase in information asymmetry translates to the scientific publication behavior of firms. Column (3) shows the results from estimating Equation (1), in which the dependent variable is the natural logarithm of one plus the number of scientific publications (*LN_PUB*). We obtain a DiD coefficient that is positive and significant at the 1% level. The point estimate in this column is 0.119, indicating that an increase in asymmetric information because of coverage shocks causes the firm to increase its scientific publications by approximately 12.6% ($= e^{0.119} - 1$) relative to the number of publications of firms with no decrease in analyst coverage. For robustness, column (4) presents the results based on the inverse hyperbolic sine transformation (*IHS_PUB*). If anything, the magnitude of the estimate becomes larger.

One concern with this estimator is that the partial effect may capture systematic differences in characteristics between the treatment and control groups. To address this concern, we add the set of control variables on the relation between analyst coverage and R&D employed by existing studies. The results, shown in columns (5)–(8), indicate that our baseline estimate is robust to controlling for a large set of time-varying observable characteristics. Across all these specifications, the estimated partial effects remain significant at the 1% level and of a similar order of magnitude. The inclusion of additional control variables has a limited impact on the estimated treatment effect, suggesting that the coverage termination is plausibly exogenous and the increase in scientific publications is not the result of omitted variable bias. It also suggests that our specifications do not suffer from a "bad control problem" (Angrist and Pischke 2009).

5.2. Additional Validation Checks

5.2.1. Matching Estimator. Another potential concern is that, if the treatment and control groups differ on observable characteristics, then they likely also differ on unobservable characteristics. If this is the case, including control variables in a linear regression framework might not adequately control for unobservable differences, especially if there are nonlinearities in the data.

To address this concern, we implement a DiD matching estimator. Our matching is similar in spirit to the approach of Irani and Oesch (2013), who match by firm size and performance. Because our purpose is to ensure that the treatment and control groups are similar in terms of the determinants of the scientific publications we match by total assets, R&D, and Q. We also match by bid–ask spreads because we hypothesize that information asymmetry affects publication rates. Finally, we match on publication growth (i.e., the growth in the number of publications from years –3 to –1), which eliminates potential remaining differential trends in the pre-event publication pattern.

We use a nearest neighbor propensity score matching procedure (He and Tian 2013, Irani and Oesch 2013). In the first step, we run a logit regression of a dummy variable equal to one if a specific firm–year is classified as treated on our matching variables. The estimated coefficients from the logit regression are used to estimate the probabilities of treatment for each firm–year. These probabilities (or propensity scores) are then used to perform a nearest neighbor match. We match with replacement, using a standard tolerance (0.005 caliper) and allowing for up to five unique matches per treated firm.

Table 3 presents the results. Columns (1) and (2) show that the coverage shock continues to have a meaningful impact on the coverage and information asymmetry of treated firms relative to those of the matched control sample. The remaining columns indicate that the DiD matching estimator produces results similar to those of the baseline in terms of both economic magnitudes and statistical significance for the scientific publication measures.

Table 3. Regressions of Corporate Publications on Analyst Coverage Shocks: Matching Estimator

Dependent variable	*COV* (1)	*BASPRD* (2)	*LN_PUB* (3)	*IHS_PUB* (4)
TREATED × *POST*	−1.073**	0.173***	0.151***	0.181***
	(0.434)	(0.060)	(0.053)	(0.063)
POST	−0.803**	−0.008	0.006	0.012
	(0.352)	(0.052)	(0.056)	(0.066)
TREATED	1.927***	−0.149**	−0.125	−0.153
	(0.487)	(0.074)	(0.092)	(0.106)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Event fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,964	4,964	4,964	4,964
Adjusted R^2	0.830	0.691	0.895	0.882

Notes. This table presents the DiD regression results of corporate scientific publications on analyst coverage shocks when balancing the sample on pretreatment covariates. The sample includes the treated and control firms assembled through the sample construction procedure described in Section 4.1 with valid matching variables in year –1. Treated firms are matched using a nearest neighbor logit propensity score match with a 0.005 caliper and with matching of up to five control firms. Robust standard errors are clustered by firm (in parentheses). Variable definitions are provided in the Online Appendix, Section A.2.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

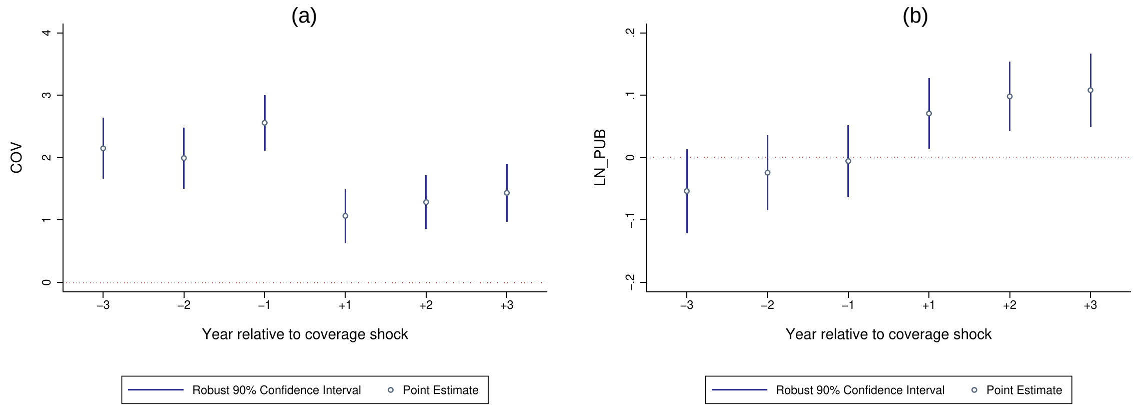
5.2.2. Dynamic Effects and the Parallel Trends Assumption. We examine whether the shock has a permanent effect on analyst coverage and the publication behavior of treated firms. In addition, we conduct falsification tests to determine whether the parallel trends assumption is violated.

Figure 1 (panel (a)) depicts the dynamic effects of the shock on analyst coverage. On the y-axis, the graph shows the number of analysts following a firm; the x-axis shows the time relative to the shock (ranging from three years prior to the shock to three years after). The vertical lines in the figure correspond to the 90% confidence intervals of the coefficient estimates. The results indicate that there are no pre-event trends in the data and coverage decreases by roughly one analyst between year –1 and year +1. Moreover, we see no postevent trends in the data and can observe that the effect of the shock on analyst coverage is permanent. This is consistent with Hong and Kacperczyk (2010) and Derrien and Kecskés (2013), who also find a permanent reduction in coverage.

Panel (b) depicts the dynamic effects of the shock on scientific publications. We see that the pre-event trend is similar for the treatment and control firms. Specifically, there is no statistically significant difference in publication rates between the treatment and control firms over the years from –3 to –1. Therefore, we fail to invalidate the parallel trends assumption, suggesting that it is not violated in our setup. We also see a permanent increase in scientific publications in the period after the shock. Especially strong is the increase between year –1 and year +1. This is intuitive under a disclosure explanation because the impact of a change in R&D disclosure behavior (in the form of scientific publications) can quickly become visible.

5.2.3. Merger/Closure Characteristics. Next, we confirm that our baseline results are not driven by broker disappearances in specific years or by the small number of mergers/closures that cause a large number of firms to be treated. Moreover, we show that our results are not driven by either broker mergers or broker closures alone and they remain robust to the exclusion of broker disappearances not included in the list provided by Kelly and Ljungqvist (2012). We tabulate the results in the Online Appendix, Table AT3.

Figure 1. (Color online) Dynamic Effects of the Analyst Shock on Coverage and Scientific Publications



Notes. This figure shows a visual DiD examination of the effect of the analyst shock on coverage and scientific publications for the treatment sample relative to the control sample from three years before the shock to three years after. Panel (a) depicts the dynamic effects of the shock on coverage. Panel (b) depicts the dynamic effects of the shock on publications.

5.3. Additional Robustness Checks and Extension

We conduct a rich set of additional tests to check the robustness of our baseline results in terms of magnitudes and statistical significance. We also consider additional publication measures to support the financial signaling interpretation. The results are tabulated in the Online Appendix, Tables AT4–AT8.

First, we rerun our DiD specification on a balanced panel to check for attrition bias. Our results are also robust to including industry-by-year fixed effects, which allow us to control for time-varying differences in scientific publishing across different industries. Throughout the paper, we use publication information from Scopus. We replicate our baseline results with data from the Web of Science and show that our results remain similar.

Second, we test whether our results suffer from serial correlation issues. To this end, we experiment with clustering standard errors at either the event or event–firm level. Using different clustering schemes makes little difference. We also repeat our DiD analysis by collapsing the firm–year observations by broker into preperiods and postperiods. This test also yields similar results.

Third, our baseline uses a three-year window before and after the coverage shock with a 12-month disappearance period. To explore the sensitivity of our results to this choice, we first move the pretreatment interval further backward by either one or two years from the event year. We also move the posttreatment window further outward by either one or two years. The DiD estimate remains robust in all these cases. Furthermore, we explore the sensitivity of the publication results to the selection of the three-year measurement window. We obtain similar results whether we use a two-, four-, or five-year window.

Fourth, we check whether our results are robust to using alternative definitions of R&D firms. We define such firms as those with at least one patent and at least one year of positive R&D during our sample period, following Arora et al. (2021). However, there might be concerns that R&D reporting in Compustat is incomplete. To this end, we relax this requirement and obtain robust results. We also show that our results remain unchanged if we require sample firms to have at least one scientific publication.

Finally, we use a series of additional publication metrics to explore the idea that increased information asymmetry because of the coverage shock not only increases the level of scientific publications, but also causes a change in their composition. First, we examine two measures of publication quality based on the number of citations received in subsequent years and the journal impact factor. Second, we look at links with university-based scientists (Audretsch and Stephan 1996). The results suggest that the treatment effects are stronger when we consider quality and/or affiliations with universities.

5.4. Heterogeneity in the Treatment Effect

5.4.1. Conditioning on Changes in Information Asymmetry and Investor Demand. We hypothesize that the analyst shock impacts publication policies by causing an increase in information asymmetry. If this is the case, changes in publication rates should be the largest for firms for which information asymmetry increases the most as a result of the shock. Similarly, if this increase in information asymmetry causes a decline in investor demand, changes in publication should be the largest for firms for which investor demand decreases the most.

To test this, we condition on changes in the following variables: analyst coverage, bid–ask spreads, the Amihud illiquidity measure, and the breadth of institutional ownership.[11] We compute these variables following Kelly and Ljungqvist (2012) and Li and You (2015). We classify firms in the top tercile of the change in the information asymmetry and investor demand proxy as having a large change and firms in the bottom tercile as having a small change. We verify that there is an economically and statistically significant decline in demand for firms that lose an analyst.

Table 4, panel A, presents the results. The effect of the shock on scientific publications is larger for firms with a larger increase in information asymmetry. Using analyst coverage as an example, the treatment effect is large in magnitude (0.202) and significant at the 1% level for firms with a large decrease in analyst coverage. In contrast, the estimated treatment effect is smaller (0.033) and insignificant for firms with a small decrease in coverage. Similarly, we see that the treatment effect is stronger for firms with a larger decrease in investor demand (0.254) than for firms with a smaller decrease in investor demand (0.018).

5.4.2. Conditioning on Financial Constraints. Derrien and Kecskés (2013) show that an increase in information asymmetry resulting from an analyst shock leads to a reduction in external financing and investment, especially for financially constrained firms. For financially unconstrained firms, the decrease in analyst coverage is largely irrelevant. Therefore, we expect more pronounced treatment effects for firms that are financially constrained.

To test this, we create subsamples of firms based on whether they are financially constrained. We begin with the delaycon measure from Hoberg and Maksimovic (2015). We consider unconstrained (constrained) firms to represent those with scores in the bottom (top) tercile. Billett et al. (2017) use two indirect proxies to classify firms as unconstrained: having a credit rating or paying dividends. Another proxy is firm age. Younger firms tend to be characterized by a higher degree of information asymmetry and high growth opportunities. We classify firms in the bottom (top) tercile of the age distribution as constrained (unconstrained).

Table 4, panel B, presents the results. The effect of the analyst shock on scientific publications is larger for firms that are financially constrained. When we use the measure from Hoberg and Maksimovic (2015), for example, the estimated marginal effect of the shock for financially constrained firms is positive and significant. The DiD coefficient is larger in magnitude (0.211) than the corresponding treatment effect for the full sample (see Table 2, column (7)) and significant at the 1% level. In contrast, the estimated treatment effect is smaller (0.087) and insignificant for financially unconstrained firms.

5.4.3. Conditioning on Proprietary Costs. We also relate firms' publication responses to proprietary costs of disclosure. Guo et al. (2004) characterize such costs in terms of the propensity of firms to patent. The authors show that firms are less reluctant to disclose extensive R&D-related information when products under development are patent-protected. We proxy for the propensity of firms to patent using the ratio of patents to R&D expenditures. We use granted patents instead of patent applications because there are concerns that patent applications can impose proprietary costs on firms (Kim and Valentine 2021). Firms in the top tercile of the propensity to patent are classified as having low disclosure costs, and firms in the bottom tercile are classified as having high disclosure costs.

The literature suggests that trade secrets and noncompete agreements increase the proprietary costs of disclosure because these agreements reduce information leakage through employee movements. Aobdia (2018) finds a negative relation between a state's propensity to enforce noncompete agreements and the disclosure activities of firms headquartered in this state. Kim et al. (2020) examine the adoption of the inevitable disclosure doctrine (IDD) by state courts and find that firms respond to IDD adoption by reducing the level of disclosure regarding R&D activities. Glaeser (2018) examines the passage of the Uniform Trade Secrets Act (UTSA) by states and finds a reduction in the disclosure of proprietary information related to trade secrets.

Following these studies, we use three proxies for firms' incentives to use trade secrecy and noncompete agreements. The first proxy is a dummy variable for whether a state has rejected (adopted) the IDD (Kim et al. 2020). The second proxy is the effective UTSA index developed by Png (2017), which measures the strength of the legal protection of trade secrets. The third proxy is the noncompete enforcement variable developed by Garmaise (2011). Firms in the bottom (top) half of these indexes are classified as having low (high) disclosure costs.

Table 4, panel C, presents the results. The effect of an analyst shock on scientific publications is larger when firms have low disclosure costs. If we consider the propensity of firms to patent, for example, the estimated treatment effect is larger in magnitude (0.207) when firms rely more heavily on patents to secure their returns to R&D and is significant at the 1% level. Among the set of firms that do not rely heavily on patents, the estimated treatment effect is smaller (0.016) and insignificant. Similarly, we observe stronger treatment effects for firms headquartered in states not enforcing noncompete agreements (0.147) than for firms headquartered in states enforcing such agreements (0.035). This is consistent with the idea that firms trade off disclosure costs against the capital market benefits when making decisions about whether to publish scientific research outcomes or keep them secret.

5.5. Alternative Perspectives

5.5.1. Other Sources of Information. Managers can potentially reduce information asymmetry by communicating information other than that about their R&D activities.

Table 4. Heterogeneity Tests

Panel A: Conditioning on an increase in information asymmetry and a decline in investor demand				
Measure Dependent variable: *LN_PUB*	Relative decrease in *COV* (1)	Relative increase in *BASPRD* (2)	Relative increase in *AMIHUD* (3)	Relative decrease in *BREADTH* (4)
TREATED × *POST* × 1(Large change)	0.202***	0.168***	0.217***	0.254***
	(0.065)	(0.047)	(0.050)	(0.056)
TREATED × *POST* × 1(Small change)	0.033	0.040	0.030	0.018
	(0.062)	(0.055)	(0.045)	(0.047)
Difference	$F = 4.50$	$F = 3.57$	$F = 7.78$	$F = 11.52$
	($p = 0.03$)	($p = 0.06$)	($p = 0.01$)	($p = 0.00$)
Controls included	Yes	Yes	Yes	Yes
Firm, year, and event fixed effects	Yes	Yes	Yes	Yes
Number of observations	74,704	71,964	71,765	76,171
Adjusted R^2	0.896	0.905	0.902	0.894
Panel B: Conditioning on pre-event financial constraints				
Measure Dependent variable: *LN_PUB*	*DELAYCON* (1)	*CREDIT_RATING* (2)	*PAYOUT* (3)	*FIRM_AGE* (4)
TREATED × *POST* × 1(Financially constrained)	0.211***	0.193***	0.185***	0.201***
	(0.048)	(0.042)	(0.047)	(0.068)
TREATED × *POST* × 1(Financially unconstrained)	0.087	0.014	0.011	−0.011
	(0.056)	(0.043)	(0.035)	(0.036)
Difference	$F = 2.85$	$F = 9.71$	$F = 9.06$	$F = 7.56$
	($p = 0.09$)	($p = 0.00$)	($p = 0.00$)	($p = 0.01$)
Controls included	Yes	Yes	Yes	Yes
Firm, year, and event fixed effects	Yes	Yes	Yes	Yes
Number of observations	80,247	121,515	121,515	85,494
Adjusted R^2	0.904	0.901	0.901	0.908
Panel C: Conditioning on pre-event disclosure costs				
Measure Dependent variable: *LN_PUB*	*PAT_INT* (1)	*IDD* (2)	*UTSA* (3)	*NON_COMP* (4)
TREATED × *POST* × 1(Low disclosure costs)	0.207***	0.135***	0.122***	0.147***
	(0.057)	(0.051)	(0.035)	(0.045)
TREATED × *POST* × 1(High disclosure costs)	0.016	−0.082	−0.021	0.035
	(0.053)	(0.079)	(0.082)	(0.040)
Difference	$F = 6.30$	$F = 5.40$	$F = 2.61$	$F = 3.61$
	($p = 0.01$)	($p = 0.02$)	($p = 0.11$)	($p = 0.06$)
Controls included	Yes	Yes	Yes	Yes
Firm, year, and event fixed effects	Yes	Yes	Yes	Yes
Number of observations	51,923	75,897	102,581	102,527
Adjusted R^2	0.900	0.901	0.902	0.902

Notes. Panel A presents the DiD regression results when conditioning on changes in information asymmetry and investor demand between the year after an analyst shock (year +1) and the year before (year –1). Firms in the top (bottom) tercile of the change in information asymmetries and investor demand are classified as having a large (small) change. We use analyst coverage (column (1)), the bid–ask spread (column (2)), Amihud's illiquidity measure (column (3)), and the breadth of institutional ownership (column (4)). Panel B presents the DiD regression results when conditioning on firms' pre-event (year –1) levels of financial constraints. For the continuous measures, constrained and unconstrained firms are divided based on the median values. We use the delaycon measure from Hoberg and Maksimovic (2015) (column (1)), whether firms have a credit rating (column (2)), whether firms pay dividends (column (3)), and firm age (column (4)). Panel C presents the DiD regression results when conditioning on firms' pre-event (year –1) disclosure costs. We consider firms' patenting intensity (column (1)) and three proxies for firms' opportunities to rely on trade secrecy and noncompete agreements (columns (2)–(4)). Robust standard errors are clustered by firm (in parentheses). The sample includes the treated and control firms assembled through the sample construction procedure described in Section 4.1. Variable definitions are provided in the Online Appendix, Section A.2.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

For instance, Balakrishnan et al. (2014) find that shocks to information asymmetry encourage managers to provide financial information in the form of earnings guidance more often.

We procure management earnings guidance from the I/B/E/S Guidance file. We include forecasts of both annual and quarterly EPS and drop observations with missing earnings announcement dates or with guidance dates occurring on or after the actual earnings announcement date. We restrict our analysis to guiding firms, that is, firms included in the I/B/E/S Guidance database that provide some earnings guidance (equivalent to the approach in Balakrishnan et al. 2014).

The results are presented in Table 5, column (1). We estimate Equation (1) with the dependent variable replaced by the natural logarithm of the amount of management earnings guidance provided during the fiscal year. The estimated treatment effect indicates that our sample firms do not provide earnings guidance more often. This is consistent with the view that for R&D firms, provision of management earnings guidance is unlikely to mitigate the consequences of an increase in information asymmetry. We conclude that financial information is not an effective substitute for R&D-related information.

5.5.2. The Dark-Side Argument. We interpret our results as consistent with a positive relation between information asymmetry and R&D disclosure. An alternative interpretation may be that shocks to analyst coverage reduce pressure on managers to meet short-term goals, which encourages them to increase long-term investments as suggested by He and Tian (2013). Given that both interpretations are possible under the main evidence, we now examine an independent implication.

In particular, if our results thus far are due to less pressure from analysts that, in turn, encourages investments in R&D, we should also observe an increase in R&D inputs and/or other R&D-related outputs caused by the shock. We report the results from this exercise in columns (2)–(7) of Table 5. Column (2) reports the regression results from estimating Equation (1) with the dependent variable replaced by R&D expenditure and shows an insignificant DiD coefficient. In column (3), the dependent variable is replaced by citation-weighted patent counts. The treatment coefficient remains small and insignificant. These findings do not support the investment explanation for our main results.

Next, we consider the use of scientific research in patents. Following Marx and Fuegi (2020), we define patents as science-based if they contain at least one citation of scientific research on their front page. We calculate the fraction of science-based patents (column (4)) and the fraction of science-based patents with external references (column (5)). Note that the construction of these variables constrains the relevant sample to firm–year observations with at least one patent. We observe patterns that are very similar to the previous results: the estimated DiD coefficients are small and statistically insignificant.

We also check whether the coverage stock causes the hiring of scientists, which is another indication of increased investments in scientific research. It does not. To demonstrate this, we leverage Scopus's unique author identifier. We define a new hire as a scientist with their first publication at a sample firm in a given year and at least one publication reflecting a different affiliation before that year. We then aggregate the sum of all new hires at a sample firm in a given year and use the natural logarithm of (one plus) this raw measure of

Table 5. Test of Alternative Perspectives

Dependent variable	*LN_GUID*	*LN_RD*	*LN_PAT*	*PAT_SCI*	*PAT_SCI_EXT*	*LN_NEW_HIRES*	*LN_NEW_HIRES*	*UNEX_EARN*
Sample	Guiding firms	Full	Full	Patenting firms$_t$	Patenting firms$_t$	Full	$\triangle$ PUBS$_{pre \rightarrow post} > 0$	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TREATED × POST	0.011	0.009	−0.007	−0.006	−0.003	−0.011	0.025	0.001
	(0.024)	(0.029)	(0.065)	(0.009)	(0.009)	(0.028)	(0.040)	(0.001)
POST	0.009	−0.003	−0.130***	−0.007	0.002	−0.000	0.101***	−0.000
	(0.008)	(0.006)	(0.024)	(0.004)	(0.004)	(0.008)	(0.021)	(0.001)
TREATED	0.011	0.051	−0.086	0.008	0.004	0.020	0.034	−0.001
	(0.025)	(0.050)	(0.089)	(0.011)	(0.012)	(0.038)	(0.069)	(0.001)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	53,127	122,429	122,429	82,335	82,335	122,429	40,885	88,073
Adjusted R^2	0.606	0.935	0.750	0.737	0.636	0.776	0.781	0.363

Notes. This table presents the DiD results of the regression of management earnings guidance, R&D expenditures, patenting, the hiring of scientists, and unexpected earnings on analyst coverage shocks. Robust standard errors are clustered by firm (in parentheses). The sample includes the treated and control firms assembled through the sample construction procedure described in Section 4.1. Variable definitions are provided in the Online Appendix, Section A.2.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

hiring. Column (6) reports estimates based on the full sample, whereas the estimates in column (7) use firms that experience an increase in scientific publications following the shock. In both specifications, we obtain weak and insignificant treatment effects.

5.5.3. The Monitoring Channel. Analysts are not only providers or interpreters of information. They can also provide monitoring and impose discipline on value-destroying managers (Irani and Oesch 2013, Chen et al. 2015). The monitoring channel has several implications. One prediction is that firms' fundamental performance should decline in response to reductions in analyst coverage as suggested by Li and You (2015). Following the authors, we use analyst forecast surprise to capture firms' fundamental performance. The results are presented in Table 5, column (8). We do not find support for the monitoring explanation for our results.

Irani and Oesch (2013) show that analyst monitoring serves as a substitute for traditional corporate governance mechanisms. Thus, a further implication of the monitoring channel is that the benefits produced by analyst monitoring should be greater for firms with weak governance. We use the same four variables for governance as Irani and Oesch (2013): the governance index, the entrenchment index, the combined CEO–chairman structure, and the dual-class share structure. We report the results in the Online Appendix, Table AT9. We find that the effect of the analyst shock on scientific publications is larger for firms with strong governance, which is also inconsistent with the monitoring explanation for our results.

What do these results mean? One interpretation is that analyst monitoring and corporate governance have a complementary rather than a substitutive relationship in R&D firms. However, additional tests indicate that the implications in Li and You (2015) hold even for the subsample of firms with strong governance. There is an alternative. Glaeser et al. (2020) show that, when managers' incentives are closely aligned with maximizing current share prices, they can be expected to disclose R&D outcomes. The intuition is that, when investors believe the manager seeks to maximize short-term stock prices, they are more likely to interpret nondisclosure as the withholding of bad news. This type of behavior takes place when governance is strong because managers face greater risk of termination in such cases (Baginski et al. 2018).[12]

6. The Effect of Scientific Publications on Investor Attention and Stock Liquidity

In this section, we provide direct evidence that scientific publications affect financial market outcomes. This complements our evidence in the previous section on brokerage house mergers and closures. The qualitative evidence from Section 3 suggests that a possible explanation for how scientific publications affect financial market outcomes is that they increase investors' attention to a firm. Merton (1987) develops a model that incorporates limited investor attention and analyzes the capital market equilibrium in this setting, including the implications for asset prices. He shows that firms with which investors are more familiar exhibit a lower cost of capital and higher share prices.

Following Da et al. (2011) and Madsen and Niessner (2019), we measure investor attention using the monthly Google Search Volume Index (GSVI). *LN_GSVI* is calculated as the natural logarithm of the GSVI. We also use a passive attention measure based on media coverage in newspapers (deHaan et al. 2015). We obtain data on news coverage from RavenPack. *LN_NEWS* is the natural logarithm of (one plus) the number of news articles about a firm published in a month. Searching and news-reading activity on Bloomberg terminals is another measure (Ben-Rephael et al. 2017). Each month, for each stock, we calculate the ratio of days with abnormal attention (i.e., the Bloomberg daily maximum attention score is three or four) (*AIAR*).

We use the following OLS regressions to examine the relation between investor attention and scientific publications:

$$Y_{i,m} = \alpha + \beta LN\_PUB_{i,m} + \gamma Z_{i,m} + \delta_m + \eta_{i,y} + \varepsilon_{i,m}, \qquad (2)$$

where i indexes the firm, m indexes the month, and $Y_{i,m}$ is the dependent variable, which is the Google search volume (*LN_GSVI*), the level of news coverage (*LN_NEWS*), or the attention measure from Bloomberg (*AIAR*). Our main variable of interest is the natural logarithm of (one plus) the monthly count of scientific publications (*LN_PUB*). Z is the vector of control variables, which includes several stock characteristics associated with investor attention. We further include firm–year fixed effects ($\eta_{i,y}$) and month fixed effects (δ_m) to control for differences across firms and months. Standard errors are clustered at the firm–year level.

Columns (1)–(6) of Table 6 present the results. All six columns indicate a positive and statistically significant relationship between scientific publications and investor attention. In terms of economic significance, a one standard deviation increase in the number of scientific publications (1.015) is associated with a 1.0% increase in Google searches for company tickers (column (2)) and a 1.1% increase in the number of news articles (column (4)). Similarly, a one standard deviation increase in the number of scientific publications is associated with a 2.8% increase in news searches on Bloomberg terminals (column (6)).

We also examine whether this increased attention has an effect on stock liquidity. To do so, we estimate Equation (2) with the dependent variable replaced by

Table 6. Regressions of Investor Attention on Scientific Publications

Dependent variable	*LN_GSVI* (1)	*LN_GSVI* (2)	*LN_NEWS* (3)	*LN_NEWS* (4)	*AIAR* (5)	*AIAR* (6)	*BASPRD* (7)	*BASPRD* (8)
LN_PUB	0.010***	0.010***	0.019***	0.011**	0.006***	0.005***	−0.006***	−0.007***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)
LN_MCAP		0.138***		0.185***		0.037***		−0.429***
		(0.015)		(0.018)		(0.007)		(0.030)
LN_AGE		−0.034		−0.021		0.019		0.120**
		(0.051)		(0.066)		(0.028)		(0.060)
LN_COV		0.010***		0.274***		0.013***		0.001
		(0.003)		(0.006)		(0.001)		(0.002)
LN_TURN		0.098***		0.323***		0.032***		−0.238***
		(0.008)		(0.010)		(0.003)		(0.017)
RET		−1.254***		−1.077**		−0.446**		4.560***
		(0.376)		(0.508)		(0.179)		(0.494)
SD_RET		2.740***		7.950***		1.183***		6.483***
		(0.244)		(0.287)		(0.117)		(0.520)
NASDAQ		−0.057		−0.100		−0.010		0.477**
		(0.108)		(0.091)		(0.039)		(0.213)
SP500		−0.026		0.060		0.030*		0.033
		(0.040)		(0.055)		(0.015)		(0.055)
Firm × Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	69,027	69,027	69,027	69,027	19,778	19,778	69,027	69,027
Adjusted R^2	0.820	0.826	0.728	0.797	0.806	0.817	0.869	0.886

Notes. This table presents OLS regression results of investor attention on the number of scientific publications. The unit of observation is the firm–month. Our initial sample includes U.S. public firms with at least one year of positive R&D expenditures and at least one patent over the period from 2004 to 2014. Our sample period begins in 2004 because Google Trends provides data on search term frequency dating back to January 2004 (https://trends.google.com/trends). Bloomberg's historical attention measure begins on 2/17/2010. Historical data are missing for the periods between 12/6/2010–1/7/2011 and 8/17/2011–11/2/2011 (Ben-Rephael et al. 2017). For this reason, the sample size is reduced when we use the Bloomberg measure. Robust standard errors (in parentheses) are clustered by firm–year. Variable definitions are provided in the Online Appendix, Section A.2.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

the bid–ask spread. We calculate this measure as the monthly average of daily bid–ask spreads. Columns (7) and (8) of Table 6 present the results. The coefficients on scientific publications are negative and statistically significant. We obtain a 1.6% decrease in the bid–ask spread relative to the sample average (0.450) with an increase in scientific publications of one standard deviation (column (8)). In sum, these results point to the channel whereby scientific publications are effective in increasing investor attention and thereby improving liquidity.

7. Conclusion

We examine how information asymmetry in financial markets affects firms' scientific disclosure behavior. We use broker closures and broker mergers to identify changes in analyst coverage that are plausibility exogenous to firm policies. Using a DiD approach, we show that a reduction in analyst coverage leads to an increase in the number of scientific publications. Moreover, the results are stronger when a decrease in analyst coverage is more costly for the firm: when information asymmetries are larger and investor demand is lower and financial constraints are present. Similarly, our results are stronger when disclosure costs are lower. Attempts to mitigate the consequences of an increase in information asymmetry is the most plausible explanation. We also show that scientific disclosure has beneficial effects on both investor attention and financial market outcomes.

Our paper contributes to the literature on the determinants of R&D disclosure by documenting how information asymmetry in financial markets affects the voluntary disclosure of scientific research. It also contributes to the literature on the consequences of R&D disclosure by documenting the relation between the voluntary disclosure of scientific research and investor attention. The paper may inform debates about the limitations and trade-offs R&D firms face in their financial market disclosure policies. It may also inform debates about why firms choose to publish scientific research and how to incentivize it. Understanding the interaction between financial markets and scientific research and the implications for the real economy is an exciting area of future research.[13]

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Endnotes

[1] We define information asymmetry as differences in information among investors, including differences in both knowledge about the firm across investors and the fraction of investors who know about the firm.

[2] In 2015, the average number of scientific publications by publicly traded firms in the United States was 19. In absolute terms, these firms have published more than 27,000 articles in academic journals (Arora et al. 2021). The Nature Index is available at https://www.natureindex.com/annual-tables/2021 (accessed October 8, 2021).

[3] See Leibniz Centre for European Economic Research, ZEW/ISI Workshop on the Exchange Between Research, Businesses and Policymaking, 2020, Panel 2: What motivates firms to publish research articles? Available at https://www.zew.de/en/zew/news/why-do-firms-publish-their-research (last accessed October 14, 2021).

[4] This is especially true for publications in the hard sciences. For instance, the median time from submission to final editorial acceptance for all Nature journals ranges between 59 and 284 days. Statistics are available at https://www.nature.cm/nature-portfolio/about/journal-metrics (last accessed February 1, 2022).

[5] Indeed, we do not find evidence of increased patenting because of asymmetric information shocks (Table 5).

[6] The Online Appendix, Figure AF1, shows broker disappearances and treated firms by calendar year.

[7] We use broker disappearances between 2000 and 2010 and examine the three fiscal years before and after each event. We also construct a 12-month "disappearance period" symmetrically around the identified events to avoid overlaps in years –1 and +1. For these reasons, the sample covers the period between 1997 and 2014.

[8] Elsevier's Scopus is also the preferred source used by the National Science Board to track scientific research trends in the United States and for international comparisons. See https://ncses.nsf.gov/pubs/nsb20206.

[9] We present the details of the extensive matching process in the Online Appendix, Section A.5.

[10] Event fixed effects refer to 43 dummies, one for each specific merger/closure event included in our sample.

[11] Although this test follows Derrien and Kecskés (2013), the evidence should be interpreted with caution because firms that produce more scientific publications have lower information asymmetry following the shock.

[12] In the Online Appendix, Table AT10, we also condition on more direct proxies for managerial career concerns and horizon: ownership by transient investors, CEO age, the expiration of the CEO's employment contract, and contracted CEO severance pay (Cziraki and Groen-Xu 2020). Consistent with our interpretation of the patterns in governance, the effect of the analyst shock on publications is larger when managers are more concerned about short-term stock prices.

[13] In a recent paper, Samila et al. (2021) examine the impact of ownership by institutional investors on the incentives of firms to invest in scientific research.

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