Does the media spotlight burn or spur innovation?

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ABSTRACT

We examine the effect of media coverage on firm innovation. Using a comprehensive sample of corporate news coverage and patenting activities over the period from 2000 to 2012, we find a negative relation between media coverage and firm innovation. Multiple identification strategies alleviate the endogeneity concern regarding the attenuation effect of media coverage on innovation. We also find supports for two economic mechanisms underlying this impact: excessive pressure on managers and the mitigation of financial constraints. Our findings provide new insights into the effect of news coverage on firms' long-term growth.

Keywords: Media coverage; Firm innovation; Managerial myopia; Patents; Citations

JEL classification: G14, G32, O31

Harvard University Professor Michael Porter, the world's leading academic strategist, noted recently, "Capital markets can be toxic to strategy." ...

The Aspen Institute echoes this sentiment. It recently issued a clarion call for "Overcoming Short-termism" that was endorsed by 28 national leaders.

– The Wall Street Journal, October 30, 2009

1. Introduction

The business media is perhaps the broadest information intermediary in capital markets. How the media affects firm value is of central interest to financial economists. According to the Gordon growth model, firm value is equal to a firm's future cash flows (c) divided by the difference between the cost of capital (k) and the long-term growth rate (g). By disclosing and disseminating information to the public, the media is known to reduce the cost of capital (k) and to protect firms' cash flows (c) against expropriation.[1] However, little is known about the media's role in firms' long-term growth (g). Given that innovation is a key determinant of long-term growth,[2] this study examines the effect of media coverage on corporate innovation.

Media coverage can impede firm innovation by imposing excessive pressure on managers or by inducing knowledge leakage to rivals. We call this statement the *spotlight-burning hypothesis*. First, market pressure leads managers to forgo long-term interests in order to boost short-term profits (Stein, 1988).[3] This view is echoed by Graham, Harvey, and Rajgopal (2005), who survey 401 chief financial officers (CFOs) in the U.S. and find that the majority of CFOs are willing to sacrifice long-term value for short-term performance because they are pressured to meet short-term earnings targets. This managerial myopia can be exacerbated by the media. The media's news dissemination function is thus a double-edged sword that increases public attention on not only the bright side but also the dark side by exposing managers to market pressure. Moreover, driven by profit-seeking incentives, the media may publish sensational articles to cater to readers (Core, Guay, and Larcker, 2008;

[1] See, for example, Klibanoff, Lamont, and Wizman (1998), Chan (2003), Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), Fang and Peress (2009), Bushee, Core, Guay, and Hamm (2010), Blankespoor, Miller, and White (2014), and Roger, Skinner, and Zechman (2016) for the media's impact on information asymmetry and therefore on the cost of capital; see, for example, Miller (2006), Core, Guay, and Larcker (2008), Dyck, Volchkova, and Zingales (2008), Joe, Louis, and Robinson (2009), Dyck, Morse, and Zingales (2010), Liu and McConnell (2013), Dai, Parwada, and Zhang (2015), and You, Zhang, and Zhang (2017) for the media's impact on corporate governance.

[2] Firm innovation has long been established by economists as one of the most important drivers of firms' long-term economic growth and competitive advantage (Solow, 1957; Romer, 1987; Hall, Jaffe, and Trajtenberg, 2005).

[3] Porter (1992) also notes: "[t]he U.S. system first and foremost advances the goals of shareholders interested in near-term appreciation of their shares – even at the expense of the long-term performance of American companies."

Gentzkow and Shapiro, 2010; Ahern and Sosyura, 2015). Compared with the typically vague description of firms' long-run growth, a news release announcing the current quarter or year's earnings attracts greater investor attention. Therefore, the media's sensational articles may primarily focus on firms' short-term performance instead of their long-term growth. Given that innovation is an output of long-term investment, the threat of media coverage can impede firm innovation. We regard this effect of media on innovation as the *market pressure channel*.

Second, the economics literature has documented that knowledge spillovers occur in the context of innovation (e.g., Jaffe, Trajtenberg, and Henderson, 1993; Jaffe, Trajtenberg, and Fogarty, 2000; Bloom, Schankerman, and Van Reenen, 2013). Specifically, one firm's investments in technology creation can engender external benefits for other firms, including competitors. Given that innovative projects are both risky and costly, the fear of knowledge leakage to rivals can discourage firms from innovating, especially in competitive industries. The media draws competitor attention to the existence of the innovation and encourages them to acquire knowledge from either public or private information channels. Therefore, media coverage can reduce firms' innovation incentives and outputs via the *knowledge spillover channel*.

Media coverage may also enhance firm innovation by allowing firms to overcome financial constraints or providing external governance. We refer to this view as the *spotlight-spurring hypothesis*. First, according to World Bank Enterprise Surveys (2006-2010), almost 40% of firms cite insufficient access to finance as the foremost obstacle to their operations and growth. Innovation is a long-term process that tends to exhaust internal capital and that entails uncertainty, which hinders effective communication with outside investors (Bhattacharya and Ritter, 1983). Innovative firms thus suffer more severely from limited external financing. The media provides a potential solution to this financial difficulty by conveying firms' inside information to the public (Tetlock, Saar-Tsechansky, and Macskassy, 2008) and increasing managers' visibility and credibility (Milbourn, 2003). Both outcomes provide firms with increased access to capital and with reduced financing costs (Fang and Peress, 2009; Bushee, Core, Guay, and Hamm, 2010; Bushman, Williams, and Wittenberg-Moerman, 2017). Therefore, we expect media coverage to increase firms' innovation outputs via this *financial constraint channel*.

Second, when the market cannot observe the full spectrum of managerial actions, moral hazard will induce managers to shirk and avoid investment in innovative projects that are risky and effortful (Bertrand and Mullainathan, 2003). Even worse, managers will divert firms' resources for their private benefits and retain less capital for investment in innovative projects. The prior literature suggests that the business media can play an important role in aligning interests between managers and shareholders by making appropriate capital allocation decisions (e.g., Liu and McConnell, 2013). This is also supported by anecdotal evidence. For example, Sears Roebuck's board was shamed as "[t]he non-performing assets of Sears" in *The Wall Street Journal* in April 1992, because of the poor performance of Sears' stock. As a response, these directors adopted many proposals advocated by a shareholder activist, which improved the firm's value by 37% in the next year (Dyck and Zingales, 2002). Thus, we expect that the monitoring role of the media can help resolve the agency problem of "lazy" or "greedy" managers and thus increase firms' investment in innovation. We view this mechanism as the *external governance channel*.

To test these two hypotheses, we use both a comprehensive database of firm-level patents and citations from Kogan, Papanikolaou, Seru, and Stoffman (2017) and United States Patent and Trademark Office Bulk Downloads, along with corporate news coverage data from RavenPack that provides us with full coverage of Dow Jones news releases. Specifically, we measure a firm's innovation outputs by using the number of citations per patent, the market value of ultimately successful patents filed by the firm in a year, as well as the number of patents. Our media coverage variable is constructed based on the number of news articles for the firm in a given year. Consistent with our *spotlight-burning hypothesis*, our baseline regression shows a negative relation between media coverage and corporate innovation outputs. The effect is not only statistically significant but also economically relevant. For example, a one-standard-deviation increase in media coverage is associated with a 7.0% decrease in citations per patent, a 14.5% decrease in patent values, and a 3.6% decrease in patent counts relative to the sample means.

Endogeneity is an important consideration in our empirical tests because the media can cater to public demand and because the extent of news coverage may be driven by the degree of sensationalism. For example, Miller (2006) finds that media outlets with a larger group of potential readers are more likely to report accounting fraud by firms. Moreover, Core, Guay, and Larcker (2008) show that negative press coverage is more severe among CEOs who have exercised more options. Similarly, in our context, the media may be more likely to cover large-sized and mature firms, which tend to have lower long-term growth and fewer innovation outputs. To substantiate our main findings, we implement a multipronged approach to mitigate the issue of endogeneity.

We first employ an instrumental variable approach. Our instrumental variable is the median travel time between a firm's headquarters and Dow Jones' eight offices. This instrumental variable is negatively associated with the extent of the firm's news coverage, because longer travel time increases the costs of collecting information and reduces media attention (Hirshleifer, Lim, and Teoh, 2009; Dai, Parwada, and Zhang, 2015). Importantly, our instrument is not directly linked to firm investment strategies or innovation outputs (Engelberg and Parsons, 2011; Gurun and Butler, 2012; You, Zhang, and Zhang 2017). The results based on the instrumental variable approach support our baseline findings.

Then, we employ the 2003 change in the Dow Jones News Services as an exogenous shock to the impact of media coverage. In March 2003, Dow Jones launched *NewsPlus*, which provides Dow Jones News subscribers with simple web-navigation techniques and makes it easier for subscribers to access and explore useful information. The new features of *NewsPlus* include: 1) more intuitive layouts and powerful search tools, 2) customizable filters to isolate content, 3) news updates on mobile devices, and 4) popup notifications for saved news searches. We document the greater effect of media coverage on innovation in the post-*NewsPlus* period, especially for firms that are highly exposed to the spotlight.

Moreover, we address the concern that the endogeneity problem can arise because poor firm fundamentals can lead to both negative news coverage and fewer investments in innovation. To address this concern, we decompose news articles into positive news coverage and negative news coverage, and we find that both positive news coverage and negative news coverage have a significantly negative impact on corporate innovation. Finally, to control for the lifecycle of a firm and mean reversion in innovation outputs, we include either the current level of innovation outputs or the change in innovation outputs in regressions. We also employ the change in change test. All these alternative specifications do not alter our conclusions.

Although the main findings suggest that news coverage has a negative effect on innovation activities in general, the observed negative effect of media may be a net outcome. In other words, the *spotlight-burning hypothesis* may dominate the *spotlight-spurring hypothesis* in the baseline analysis. To further disentangle the two hypotheses, we perform additional tests to examine the mechanisms through which media coverage affects firm innovation. First, we decompose our news coverage measure into several news sub-components based on news categories, namely, earnings-related news coverage, product and innovation-related news coverage, financing-related news coverage, and governance-related news coverage. Consistent with the *market pressure channel* and the *financial constraint* *channel*, innovation outputs decrease with earnings-related news coverage while they increase with financing-related news coverage.

Second, we conduct further analyses by examining the interaction terms between news coverage sub-components and several channel-related factors. For example, we use the weighted average of the churn rates of institutional investors holding the firm (Gaspar, Massa, and Matos, 2005) as the proxy for market pressure, and calculate the Whited and Wu's (2006) index to measure a firm's external finance constraints. Consistent with the two channels, we find that the negative effect of earnings-related news coverage is stronger for firms with a larger proportion of short-term institutional investors, while the positive effect of financing-related news coverage is more pronounced for firms with greater financial constraints.

In the final part of our study, we implement a series of additional tests to further enrich our main findings. First, we construct a measure of the productivity of innovators and find that the main impeding effect of media coverage is not driven by its effect on low-productivity innovators. Second, we find that not only patenting activities, but also a firm's general growth prospects, are attenuated by media coverage. Finally, we show that our main findings are robust to the use of various measures of innovation outputs and news coverage, different sample selections, alternative clustering techniques, and other news data source.

Our study contributes to two strands of literature. First, we add to the literature on the real effects of the media. In their seminal papers, Zingales (2000) and Dyck and Zingales (2002) propose that the media plays a significant role in affecting corporate policies and guiding firms in resource allocation decisions. This role can be either positive or negative. For example, the literature recognizes the business media's positive role in detecting accounting fraud (Miller, 2006; Dyck, Morse, and Zingales, 2010), reversing governance violations (Dyck, Volchkova, and Zingales, 2008), exposing board ineffectiveness (Joe, Louis, and Robinson, 2009), monitoring executive compensation (Kuhnen and Niessen, 2012), limiting the use of dual class shares (Braggion and Giannetti, 2013), influencing managers' capital allocation decisions (Liu and McConnell, 2013), disciplining insiders' transactions (Dai, Parwada, and Zhang, 2015), and increasing the chance of forced CEO turnover (You, Zhang, and Zhang, 2017). Only a few papers provide evidence of the dark side of media coverage. For example, Core, Guay, and Larcker (2008) show that the media engages in sensationalism and that firms do not respond to the negative tones of media coverage by reducing excess CEO compensation or increasing CEO turnover. Moreover, Gurun and Butler (2012) find that a positive media slate is associated with firms' local media advertising expenditures. By linking media coverage with firm innovation, our paper is among the first to show the negative effects of media coverage on firms' long-term growth.[4]

Second, we contribute to the growing literature on finance and innovation. Specifically, empirical evidence shows that laws (Acharya and Subramanian, 2009; Acharya, Baghai, and Subramanian, 2014), financial market liberalization (Moshirian, Tian, Zhang, and Zhang, 2015), foreign institutional ownership (Luong, Moshirian, Nguyen, Tian, and Zhang, 2017), firm boundaries (Seru, 2014), stock liquidity (Fang, Tian, and Tice, 2014), financial analysts (He and Tian, 2013), managerial contracts (Ederer and Manso, 2013), product market competition (Aghion, Bloom, Blundell, Griffith, and Howitt, 2005), and corporate venture capital (Chemmanur, Loutskina, and Tian, 2014) all significantly affect innovation. However, there is little insight into the role of media coverage in encouraging or impeding innovation. We fill this gap by showing that the media can be the key factor that determines managers' innovation decisions.

The remainder of the paper proceeds as follows. We develop our hypotheses in Section 2. Section 3 describes the data sources and variable construction. We present the main findings in Section 4 and the results of additional tests in Section 5. Section 6 concludes the paper.

2. Hypothesis development

Serving as a powerful market force, the media can pressure managers to forgo long-term investments in exchange for short-term performance (Stein, 1988). Top U.S. executives admit that when they are under pressure to meet or beat earnings targets, they are willing to sacrifice long-term firm value (Graham, Harvey, and Rajgopal, 2005), especially when there is a lack of commitment to long-term contract of managerial compensation (Manso, 2011). Moreover, the media may publish sensational articles to cater to readers' interests (Core, Guay, and Larcker, 2008; Gentzkow and Shapiro, 2010; Ahern and Sosyura, 2015). Given that coverage of firms' short-term performance is usually more eye-catching than that of firms' long-term growth, the media's sensational articles may primarily focus on firms' short-term performance instead of their long-term growth prospects. The threat of biased media coverage of earnings and other short-term performance indicators thus exacerbates

[4] Previous studies argue both that firms choose to disclose less information to the market because of proprietary costs (e.g., Verrecchia, 1983; Li, 2010) and that enforcing more corporate disclosure may have a negative effect on firms' information environments (e.g., Skinner, 2003). Our study adds to this literature by showing that the overwheling information reported by the media can indeed affect firms' real decisions and negatively affect firms' long-term growth prospects.

managerial short-termism, leading to reduced long-term corporate investment. Thus, we posit that the media can impede firms' innovation activities through this *market pressure channel*.

Moreover, the prior economics literature provides evidence of knowledge leakage in the context of patenting activities. For example, Jaffe, Trajtenberg, and Henderson (1993) find that the costs of acquiring knowledge, proxied by the geographic distance between two innovators, influence the likelihood of technology spillover. In a survey study, Jaffe, Trajtenberg, and Fogarty (2000) suggest that knowledge leakage can occur from innovators to other parties, such as competitors. Bloom, Schankerman, and Van Reenen (2013) further show that knowledge leakage among rivals can negatively affect firm value. As information intermediaries, the media might draw attention to the existence of innovation and encourage competitors to acquire the information some other way. We regard this mechanism as the *knowledge spillover channel*. Through this channel, managers can be discouraged from innovating when firms are highly exposed in the media spotlight because knowledge leakage, especially in competitive industries, may induce external benefits for competitive firms.

Considering the above discussion, we develop our first hypothesis (H1), the *spotlight-burning hypothesis*, through both the *market pressure channel* and the *knowledge spillover channel* and make the following prediction:

H1: Media coverage is negatively associated with firms' innovation outputs.

Conversely, media coverage may enhance firm innovation by alleviating financial constraints and imposing external governance. Innovation is a long-term, uncertain process with a substantial likelihood of failure (Holmstrom, 1989). Firms that invest heavily in innovative projects are subject to substantial information asymmetry (Bhattacharya and Ritter, 1983), and they are more likely to encounter severe financing constraint problems. The difficulties in conveying the promising prospects of long-term projects to the market allow bad firms to mimic the investment decisions of good firms, thus creating a lemon problem (Myers and Majluf, 1984; Trueman, 1986): good firms either overinvest as a signal (Bebchuk and Stole, 1993) or underinvest completely, depending on the preference of the market (Brandenburger and Polak, 1996).

Effective communication between managers and outside investors through information intermediaries can reduce information asymmetry, increase visibility, and thus resolve financial constraint problems. On the one hand, prior studies have documented the media's impact on stock price by conveying inside information to the public (Klibanoff, Lamont, and Wizman, 1998; Chan 2003; Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008).

On the other hand, the media could help attract more investors or partners due to increased managers' visibility, and lend credibility to their investment decisions and viability (Milbourn, 2003; Falato, Li, Milbourn, 2015). Following these studies, recent research has shown that media coverage reduces financing and transaction costs (Fang and Peress, 2009; Bushee, Core, Guay, and Hamm, 2010; Blankespoor, Miller, and White, 2014; Bushman, Williams, and Wittenberg-Moerman, 2017). Therefore, we conjecture that media coverage can encourage investment in innovative projects by reducing financial constraints. We call this mechanism underlying the positive impact of media on innovation the *financial constraint channel*.

Finally, given that outside investors cannot observe firms' full set of potential projects, managers tend to steer their investment decisions toward projects that are less risky and effortful (Bertrand and Mullainathan, 2003). Under severe moral hazard, managers can even consume firms' resources for private benefits at the cost of long-term growth (Narayanan, 1985; Stein, 1988; Benmelech, Kandel, and Veronesi, 2010). The existing literature has documented that in general the business media plays an important role in disciplining managers to mitigate agency costs (Miller, 2006; Dyck, Volchkova, and Zingales, 2008; Joe, Louis, and Robinson, 2009; Dyck, Morse, and Zingales, 2010; Kuhnen and Niessen, 2012; Braggion and Giannetti, 2013; Dai, Parwada, and Zhang, 2015; You, Zhang, and Zhang, 2017). In particular, Liu and McConnell (2013) find that the media encourages managers to make appropriate investment decisions in takeover markets. Therefore, we expect the media to exert a positive effect on innovation investment through this *external governance channel*, given managers' tendency to select less risky and effortful projects.

In sum, we develop our hypothesis (H2), the *spotlight-spurring hypothesis*, based on both the *financial constraint channel* and the *external governance channel* and make the following prediction:

H2: Media coverage is positively associated with firms' innovation outputs.

3. Research design

3.1. Data sample and sources

We estimate news coverage by using RavenPack, a comprehensive news database that has been widely used in the literature (e.g., Kolasinski, Reed, and Ringgenberg, 2013; Dang, Moshirian, and Zhang, 2014; Shroff, Verdi, and Yu, 2014; Dai, Parwada, Zhang, 2015; Rogers, Skinner, and Zechman, 2016; Wang, Zhang, and Zhu, 2017). RavenPack consists of two news sources, namely, the Dow Jones Edition (available from January 1, 2000) and the

Web Edition (available from January 1, 2007). The Dow Jones Edition covers real-time, firm-level news articles from leading news providers such as *Dow Jones Newswires*, *The Wall Street Journal*, *Barron's*, and *MarketWatch* while the Web Edition collects news articles from other major publishers and web aggregators, including industry and business publications, regional and local newspapers, blog sites, government and regulatory updates, and trustworthy financial websites.

We measure corporate innovation based on the U.S. firm patent data provided by Kogan, Papanikolaou, Seru, and Stoffman (2017, hereafter KPSS) ending in 2009. KPSS construct the dataset by downloading a history of U.S. patent documents from Google Patents (https://patents.google.com). This patent search engine includes patent applications and grants from the United States Patent and Trademark Office (USPTO). Other studies using Google Patents include Moser and Voena (2012) and Moser, Voena, and Waldinger (2014). After identifying the assignee name for each patent in Google Patents, KPSS match these patents to firms from the CRSP and construct a sample with firm coverage similar to the NBER Patent Citation database.[5] To further extend our sample period, we complement the KPSS data with the patent data from 2010 to 2012 collected from USPTO Bulk Downloads (https://pairbulkdata.uspto.gov).

Our initial sample starts with a comprehensive dataset of corporate news coverage and patenting activities over the period from calendar year 2000 to 2012 for U.S. stocks listed on the NYSE, Amex, and Nasdaq. This sample is a matching outcome between data from RavenPack available from 2000 to 2010 and combined KPSS and USPTO Patent data from 2002 to 2012. We relate the media coverage variables in the current year t to innovation outcome variables two years ahead ($t+2$) in order to account for the long-term nature of innovation processes. In robustness tests reported in the Internet Appendix, we also use a three-year lead period to match the innovation outcome variables with news coverage metrics and find that our conclusions remain the same.

Next, we merge Compustat and the initial RavenPack-Patent sample and require a firm to be covered by the media for at least once during our sample period. This results in a combined sample that comprises 52,955 firm-year observations. Further, as illustrated in

[5] NBER Patent Citation database covers the period 1976-2006. By utilizing information after 2006, KPSS provides more accurate data of patents and citations, especially after year 2000. For example, in the KPSS database, there are 1,808 unique listed firms successfully filing 80,967 patents in year 2003. In contrast, there are only 1,338 unique listed firms successfully filing 42,315 patents in the NBER Patent Citation database in year 2003. The online appendix of KPSS (2017) provides more details regarding the two databases.

Table 1, we take the following steps to filter the sample: (1) drop regulated industries with SIC Codes either between 4900 and 4999 or between 6000 and 6999;[6] (2) remove observations with missing values for the control variables; and (3) exclude firms without information about bid-ask spreads from the CRSP. The final sample for main analyses comprises 36,782 firm-year observations with the media coverage variables calculated in year *t* from 2000 to 2010 and with the innovation outcome variables estimated in year *t+2* from 2002 to 2012.

Moreover, we obtain the accounting information from Compustat, institutional ownership data from Thomson Reuters Institutional Holdings, and analyst data from I/B/E/S. To construct our instrumental variables, we use location information for firm headquarters from Compustat, location information for Dow Jones' U.S. offices from the Dow Jones website, and the detailed information on flights between firm headquarters and Dow Jones' offices from the U.S. Department of Transportation T-100 Segment Data. Due to the missing information for firm headquarters, the sample for instrumental variable analyses consists of 34,642 firm-year observations. In analyses of the economic channels through which media coverage affects corporate innovation, we construct channel variables by using additional data sources such as product market competition data from Hoberg, Philips, and Prabhala (2014) and corporate governance information from BoardEx.

[Insert Table 1 Here]

3.2. Variable construction

We measure firm's overall news coverage ($News_t$) as the number of news articles of firm *i* in calendar year *t*, and scale $News_t$ by 100 in the regression analysis. First, we exclude firm-initiated press releases that are initiated by firms in the estimation of $News_t$. Then, we require the Relevance Score provided by RavenPack to be 100 for each news article, which indicates that a firm linked to the article is prominent and plays a key role in the news story as identified by RavenPack. Furthermore, because RavenPack classifies news articles into various types by using proprietary text and part-of-speech tagging or labeling, the news

[6] Consistent with the majority in the literature, we include all firms except for those in utilities or financial industries in our main analysis (e.g., He and Tian, 2013; Fang, Tian and Tice, 2014; Cornaggia, Mao, Tian, and Wolfe, 2015; Mukherjee, Singh, and Žaldokas, 2017). In Panel B of Table 3, we provide consistent results with different sampling filters. These filters include firms with positive R&D expenditure, firms with non-missing R&D expenditure, manufacturing firms only, and patenting firms only.

category information allows us to trace news articles related to our four economic channels through which the media effect operates. Accordingly, we decompose the overall news coverage into four sub-components, namely, earnings-related news coverage ($News_{Earnings,t}$), product and innovation-related ($News_{Product,t}$), governance-related news coverage ($News_{Governance,t}$), and financing-related news coverage ($News_{Financing,t}$).[7] Figure 1 presents the distribution of news categories adopted in our study from RavenPack.

We define three metrics of innovation productivity in calendar year t+2. $CitaPat_{t+2}$ is the average number of citations per patent for ultimately successful patents filed by a firm in year t+2.[8] $PValue_{t+2}$ is the sum market value of successful patents filed in year t+2 scaled by the market value of equity for following the approach of KPSS.[9] $Patent_{t+2}$ is the number of ultimately successful patents filed by a firm in year t+2. These measures have been widely used in the innovation literature as observable innovation outputs (e.g., Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Nanda and Rhodes-Kropf, 2013; KPSS, 2017), and they successfully capture three dimensions of innovation outputs: quality, value, and quantity. The logarithm values of these innovation metrics are used in regression analyses. In robustness tests, we perform our analyses by using alternative innovation metrics for which the variable definitions and results are reported in Tables IA1 to IA3 of the Internet Appendix.

Following the literature, we include as control variables firm and industry characteristics estimated in year t that affect corporate innovation outcomes (e.g., He and Tian, 2013; Fang, Tian, and Tice, 2014): $Assets_t$, the logarithm value of the book value of total assets; $R\&D_t$, research and development expenses scaled by assets; Age_t, the logarithm value of firm age in years; ROA_t, net income scaled by assets; PPE_t, the net value of property, plant and equipment scaled by assets; $Leverage_t$, the sum of debt in current liabilities and long-term debt scaled by assets; $Capex_t$, capital expenditures scaled by assets; $TobinQ_t$, the ratio of the market value to the book value of assets; $KZIndex_t$, the Kaplan and Zingales (1997) financial

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[7] Earnings-related news articles include, for example, those related to "earnings-above-expectations", "earnings-below-expectations", and "earnings-meet-expectations", which highlight the media's focus on short-term performance. Product and innovation-related news articles cover both "product" news and "patent" news. Governance-related news articles include articles related to "insider trading", "fraud", "board-meeting", "executive appointment", "executive compensation", and so on. Finally, financing-related news articles are related to "debt", "debt restructuring", and "credit rating".

[8] Number of citations per patent is adjusted for truncation, where the raw value is divided by the sample annual mean (Hall, Jaffe, and Trajtenberg, 2001).

[9] KPSS estimate the patent value based on market adjusted return in a window [0, 2] following patent grant day zero, taking into account the number of multiple patents filed on the same day, the firm market capitalization, and the volatility of firm returns. See more details regarding the estimation of patent value in Section 2.4 of KPSS (2017).

constraint index; $Hindex_t$ and $Hindex^2_t$, the Herfindahl index of two-digit SIC industries using sales data and its square term; $InstOwn_t$, shares owned by institutions scaled by total shares outstanding (Aghion, Van Reenen, Zingales, 2013); $Analyst_t$, the natural logarithm of one plus the number of analysts issuing annual earnings per share (EPS) forecasts; and $Spread_t$, the average daily bid-ask spread estimated based on the CRSP according to Corwin and Schultz (2012). See Appendix for detailed variable definitions.

[Insert Figure 1 Here]

3.3. Summary statistics

Table 2 reports the descriptive statistics of the main variables in our baseline model for the sample of 36,782 firm-year observations. All of the continuous variables are winsorized at the 1 and 99 percent levels. The mean, median, and 90th percentile values of $CitaPat_{t+2}$ are 1.42, zero, and 4.00, respectively. Consistent with the innovation literature (e.g., He and Tian, 2013), these results indicate that the distribution of this measure is right skewed. Similarly, the distributions of $PValue_{t+2}$ and $Patent_{t+2}$ are also right skewed as shown in Table 2, where $PValue_{t+2}$ is multiplied by 100 for the sake of exposition. That is, both have mean values equal to 1.38 and 7.67, median values equal to zero, and 90th percentile values equal to 4.51 and 7.00, respectively.

Regarding $News_t$, an average firm is reported for 66.26 times per year, and the median value is 39.00. Figure 2 shows the distribution of news coverage across sub-groups of firms split into quintiles by firm size ($Assets_t$). The mean value of $News_t$ for firms in the largest size group (Quintile 5) is 159.68, and that for firms in the smallest size group (Quintile 1) is 23.09, indicating that even for smaller firms they still have fairly good exposure in the media spotlight in our sample. Similarly, the average value of $Patent_{t+2}$ is 29.13 (0.35) for firms in Quintile 5 (Quintile 1). These results also suggest that both news coverage and the number of patents increase with firm size, for which we should control in our analyses together with other fundamentals that can affect media reports and innovation outputs. Moreover, we find that the control variables reported in Table 2 have distributions that are consistent with the literature. For example, on average, R&D expenses account for 6.10 percent of total assets, firm age is approximately 18.81 years, Tobin's Q is 2.10, and a firm is covered by 5.43 analysts.

[Insert Table 2 Here]

4. Results

4.1. Baseline findings

In this section, we examine the effect of media coverage on corporate innovation. Following the two strands of the literature on the effects of media coverage and the determinants of innovation outputs, we specify our baseline model as follows: [10]

$$Innovation_{t+2} = \alpha + \beta_{News}\, News_t + \beta_{CV}\, Control\ Variables_t + \beta_{FE}\ Fixed\ Effects + \varepsilon, \qquad (1)$$

where $News_t$ is our main variable of interest estimated in year t and $Innovation_{t+2}$ denotes the logarithm-transformed innovation measures, i.e., $Log\ (CitaPat_{t+2} + 1)$, $Log\ (PValue_{t+2} + 1)$, and $Log\ (Patent_{t+2} + 1)$, estimated in year $t+2$. We expect the coefficient on $News_t$ to be significantly negative (positive) based on our *spotlight-burning hypothesis* (*spotlight-spurring hypothesis*). In Equation (1), $Control\ Variables_t$ represents the vector of control variables of firm and industry factors as described in Section 3.2. We also include firm and year fixed effects to control for cross-sectional and time-series omitted factors and cluster standard errors at the firm level.

We present the results of our main analysis in Table 3. In Model (1), the coefficient on $News_t$ for $CitaPat_{t+2}$ is significantly negative (-0.062, *t*-stat = -4.71), suggesting that the quality of corporate innovation is attenuated by media coverage. This result is consistent with the *spotlight-burning hypothesis*. The coefficient is also economically significant. For example, a one-standard-deviation increase in $News_t$ is associated with a 7.0% decline in the citation per patent at the sample mean.[11]

Similar results are reported in Models (2) and (3), in which we regress $Log\ (PValue_{t+2}+1)$ and $Log\ (Patent_{t+2}+1)$ on $News_t$ (coefficients = -0.127 and -0.078, *t*-stat = -8.11 and -3.35, respectively). These findings indicate that not only the quality, but also the value of patents, measured by the total market value of granted patents, and the quantity of patents, measured by the total number of patents filed and granted, are negatively associated with media

[10] See, for example, the papers related to the impact of media on executive compensation (Core, Guay and Larcker, 2008; Kuhnen and Niessen, 2012) and on limited voting shares (Braggion and Giannetti, 2013).

[11] Based on the summary statistics in Table 2, the economic impact of $News_t$ on $Log\ (Patent_{t+2}+1)$ = (-0.063×0.990) / log (1.424+1) = -7.0%, where the standard deviation of $News_t$ is 0.990 (divided by 100) and the mean value of $Patent_{t+2}$ is 1.424.

coverage.[12] In terms of economic magnitude, a one-standard-deviation increase in *$News_t$* leads to 14.5% (3.6%) decrease in *$PValue_{t+2}$* (*$Patent_{t+2}$*) at the mean value.[13]

Following the majority in the literature (e.g. He and Tian, 2013; Fang, Tian and Tice, 2014; Cornaggia, Mao, Tian, and Wolfe, 2015; Mukherjee, Singh, and Žaldokas, 2017), we include both patenting and non-patenting firms in our main analyses. We repeat our analyses using alternative sample selection criteria to sustain the robustness of our results. Specifically, we exclude firms that are possibly non-innovators because of the fundamentals of their business, and those for which patent generation may not play a key role in innovation and growth.

The results are reported in Panel B of Table 3. We conduct the analyses for firms with positive R&D expenses in year *t* in Models (1) to (3), for firms with R&D expenses recognized for at least once during the sample period in Models (4) to (6), for firms incorporated in manufacture industries (SIC Codes 2000-3999) in Models (7) to (9), and for firms with non-missing patenting information in at least one year throughout the sample period in Models (10) to (12). Consistently, we find that the negative and significant effect of news coverage on innovation outcomes holds across all these sub-samples.

Overall, we find a negative effect of media coverage on corporate innovation, which suggests that the *spotlight-burning hypothesis* dominates the *spotlight-spurring hypothesis* in predicting the effect of media coverage on firms' innovation activities.

[Insert Table 3 Here]

4.2. Endogeneity tests

Our media coverage variable *$News_t$* is unlikely to occur randomly (Engelberg and Parsons, 2011). If media coverage and innovation outputs are jointly determined by unobservable firm characteristics, our prior results may be subject to an endogeneity concern. In this section, we adopt multiple approaches to alleviate this endogeneity concern.

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[12] Although we find a strong relation between *$News_t$* and *$Innovation_{t+2}$*, the incremental R^2s due to news coverage are not large (0.24%, 1.21%, and 0.11% increases in *Adjusted R^2* for *$CitaPat_{t+2}$*, *$PValue_{t+2}$*, and *$Patent_{t+2}$*, respectively). This suggests that news coverage does not explain the majority of innovation variation, and provides comfort that our model does not omit a critical variable.

[13] The economic impact of *$News_t$* on *Log ($PValue_{t+2}$+1)* = (-0.127×0.990) / log (1.375+1) = -14.5%, where the standard deviation of *$News_t$* is 0.990 (divided by 100) and the mean value of *$PValue_{t+2}$* is 1.375. Similarly, the economic impact of *$News_t$* on *Log ($Patent_{t+2}$+1)* = (-0.078×0.990) / log (7.674+1) = -3.6%, where the standard deviation of *$News_t$* is 0.990 (divided by 100) and the mean value of *$Patent_{t+2}$* is 7.674.

4.2.1. Instrumental variable analysis

We first conduct a two-stage instrumental variable analysis, as set forth below, to address the endogeneity concern:

$$News_t = \alpha + \beta_{IV} IV_t + \beta_{CV} Control\ Variables_t + \beta_{FE}\ Fixed\ Effects + \varepsilon, \tag{2}$$

and

$$Innovation_{t+2} = \alpha + \beta_{News\ Predicted} News_{Predicted\ t} + \beta_{CV} Control\ Variables_t + \beta_{FE}\ Fixed\ Effects + \varepsilon, \tag{3}$$

where we include the same set of control variables as in Equation (1) as well as industry and year fixed effects. Standard errors are again clustered at the firm level. We regress $News_t$ on our instrumental variable (IV_t) in the first-stage regression and then use the predicted value of $News_t$ in the second-stage regression.

Our instrument is $TravelTime_t$, which is the median value of the number of minutes for travel between a firm's headquarters and Dow Jones' eight offices in year t, scaled by 100 in regression analysis.[14] We expect the travel time between the firm's headquarters and Dow Jones' eight offices to have a negative impact on media coverage for two reasons. First, Gurun and Butler (2012) and You, Zhang, and Zhang (2017) find that a firm's media coverage and the content of such coverage are dependent on the distance between the firm and news outlets. To the extent that journalists incur higher costs by collecting and analyzing information from distant firms, longer travel time lowers the likelihood of news coverage. Second, a long travel time between news outlets and the firm can reduce the media's attention and interest in following the firm. More importantly, there is no theory or evidence that the travel time between the firm's headquarters and Dow Jones' eight offices affects the firm's innovation outputs. Therefore, $TravelTime_t$ meets both relevance and exclusion conditions, and it can serve as a valid instrument for $News_t$.

Following Giroud (2013), the number of minutes for travel between the firm's headquarters and one of the eight Dow Jones offices is computed under the assumption that travelers (e.g., news reporters) optimally choose the route and means (e.g., car, or plane) of transportation. We use five-digit ZIP codes to identify the location of firms' headquarters, Dow Jones offices, and airports. Following Huber and Rust (2016), we first use the Open

[14] The eight Dow Jones offices are at Boston, Chicago, Minneapolis, New York, Princeton, San Francisco, Waltham and Washington. See http://www.dowjones.com/contact.

Source Routing Machine (OSRM) and Open-Sourced Maps (http://www.openstreetmap.org) to calculate the travel time by car between the firm' headquarters and Dow Jones' eight offices. Second, we identify the largest nearby airport for each Dow Jones office and the airport nearby each firm's headquarters.[15] Third, we calculate the fastest airline route between the firm' headquarters and Dow Jones' eight offices by summing up three components: (1) the travel time by car from the firm' headquarters and its nearby airport, (2) the duration of the flight and layover time, and (3) the travel time by car from the Dow Jones offices' nearby to the Dow Jones' offices.[16] Finally, by comparing the travel time by car with that by airplane, we use the shorter one to construct our *TravelTime* variable.

We use the following example to illustrate the construction of our instrument variable. ADC Telecommunications is a communication firm located in Eden Prairie, Minnesota (ZIP code 55343). We have two options to estimate the travel time between this company and Dow Jones' Boston office in 2006. The first choice is that we can drive from Eden Prairie to the Boston office directly. As shown in the upper half of Figure 3, this choice will take us about 24 hours according to OSRM. Alternatively, we can first drive from Eden Prairie to Minneapolis airport (driving time about 19 minutes), take a flight operated by Northwest Airlines (ramp-to-ramp time about 2 hour 45 minutes), and then drive from Boston airport to Dow Jones' Boston office (driving time about 8 minutes). As shown in the bottom half of Figure 3, this choice will take us about 3 hour 12 minutes. Comparing the two choices, we use the second and faster route, so the value that we use to estimate our instrument variable, *TravelTime*, is 3 hour 12 minutes in this example.

[Insert Figure 3 Here]

In Panel A of Table 4, we provide information regarding nearby airports for each Dow Jones office, the average travel time (in minutes) from the firm's headquarters to each Dow Jones office and the percentage of means of transportation. On average, it takes around four hours to travel from the firm's headquarters to the Dow Jones office, varying from 201 minutes for the Dow Jones office in Chicago to 313 minutes for that in San Francisco. In general, more than 90% of the transportation involves airplane, and more than 80% of the transportation relies on at least one transfer flight (i.e., at least taking two flights). The

[15] It always results in an increase in travel time by using alternative airports for the Dow Jones offices.

[16] Following Giroud (2013), we use ramp-to-ramp time from the U.S. Department of Transportation T-100 segment data to measure flight duration and assume a 60-minute layover time for transfer flight.

Princeton office has the largest proportion of merely car driving (15.55%), while the Minneapolis office mostly involves the most transportation by flight (97.00%).

We conduct the instrumental variable analyses in Panel B of Table 4. Specifically, in the first stage, we regress $News_t$ on $TravelTime_t$ in year t to estimate the predicted value of news coverage, $News_{Predicted\ t}$. In the second stage, we then use $News_{Predicted\ t}$ as our variable of interest in determining $Innovation_{t+2}$. Model (1) presents the result of the first-stage regression. As predicted, $TravelTime_t$ is negatively and significantly associated with $News_t$ (coefficient = -0.030, t-stat = -2.96), and a one-standard-deviation increase in $TravelTime_t$ leads to a 5.0% decrease in news coverage relative to the mean value.[17] The Cragg-Donald F statistic is 64.44, which suggests that $TravelTime_t$ is not a weak instrument (Cragg and Donald, 1993).[18] Throughout Models (2) to (4), we present the results of the second-stage regression for the three innovation variables. We find that the coefficients on $News_{Predicted\ t}$ are negative and significant, which supports the baseline finding that media coverage impedes corporate innovation.

[Insert Table 4 Here]

4.2.2. Natural experiment

To further mitigate the endogeneity concern on the relation between the media and innovation, we employ the introduction of *NewsPlus* as an exogenous shock to the impact of media coverage. In 2003, the Dow Jones News Services launched a new product, *NewsPlus*. This is a platform designed for quick navigation and seamless news streaming. The new features of *NewsPlus* include: 1) more intuitive layouts and powerful search tools to navigate news stories, 2) customizable filters to isolate and sort the content which interests subscribers, 3) news updates on mobile devices based on customization of filters ported from desktops, and 4) popup notifications for updates to saved news searches.[19] See a vivid illustration for *NewsPlus* (https://www.dowjones.com/products/newswires/newsplus) in Dow Jones website and Figure 4 for the snapshots from this illustration regarding the key features of *NewsPlus*.

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[17] The economic impact of $TravelTime_t$ on $News_t$ = (-0.030×1.143) / 0.686 = -5.0%, where the standard deviation of $TravelTime_t$ is 1.143 and the mean value of $News_t$ is 0.686 in the sample for instrumental variable analyses (both scaled by 100).

[18] The critical value of the Stock-Yogo test is 16.38 for 10% maximal IV size (Stock and Yogo, 2005).

[19] Other product features of *NewsPlus* include: 1) quick reference for synopses of stocks, bonds, currencies and commodities, and 2) market overview for financial markets summary including futures and currencies.

All these enhancements enable the subscribers of Dow Jones News Services to easily access not only relevant, but critical information, beyond thousands of daily news articles. More importantly, the enhancement is provided to the subscribers of Dow Jones News Services at no additional cost. The team of Dow Jones Newswires introduced *NewsPlus* in an extremely positive tone: "*Our mutual subscriber base of financial advisors, wealth managers, brokers and other investment professionals will find that Dow Jones NewsPlus is a valuable tool that makes it easier to access and use the news that's critical to their practices and customers*." Taken together, we expect the effect of news coverage on innovation to be more pronounced after the launch of *NewsPlus,* which facilitates the news dissemination process, especially for firms which are more highly exposed in the spotlight.

[Insert Figure 4 Here]

We conduct the analyses for this quasi-experiment in a subsample period from 2000 to 2005. We first define $Post_{NewsPlus}$ as a dummy variable equal to one if year t is between 2003 and 2005, otherwise zero for years 2000 to 2002. Then, we add the interaction between $News_t$ and $Post_{NewsPlus}$ in our baseline models and expect the coefficients on $News_t \times Post_{NewsPlus}$ to be negative and significant. Furthermore, we focus on firms with high media coverage and expect the quasi-experiment effect to be stronger for these highly-media-exposed firms, i.e., significantly negative coefficients on $News_t \times Post_{NewsPlus} \times News_{High}$, where $News_{High}$ is a dummy variable equal to one if a firm has news coverage above the sample median in year t.

The results are presented in Table 5. Consistent with our prediction, the negative impact of media coverage on innovation becomes stronger after the implementation of *NewsPlus* in Models (1) to (3) (coefficients on $News_t \times Post_{NewsPlus}$ = -0.034, -0.042, and -0.070, t-stats = -1.72, -2.94, and -3.19, respectively). We further show that after the implementation of *NewsPlus,* the impact of media coverage becomes even stronger for firms with news coverage above the sample median in Models (4) and (6) (coefficients on $News_t \times Post_{NewsPlus} \times News_{High}$ = -0.390 and -0.646, t-stats = -3.23 and -3.76 for $CitaPat_{t+2}$ and $Patent_{t+2}$). Therefore, the evidence from the above analyses further confirms that the negative impact of media on innovation outcomes is intuitively meaningful.

[Insert Table 5 Here]

4.2.3. Other endogeneity tests

In this section, we conduct a series of additional tests to further address the endogeneity concern. These tests involve separating positive news from negative news, controlling for past innovation outcomes, and adopting a change-in-change specification.

First, our main findings regarding the negative effect of media on innovation may be subject to an alternative interpretation. That is, firms with poor fundamentals are associated with more negative news coverage, and those firms in turn make fewer investments in innovative projects. To address this concern, we decompose $News_t$ into $News_{Positive,t}$ and $News_{Negative,t}$, which are the numbers of positive and negative news articles for firm *i* in year *t*. Following Bushman, Williams, and Wittenberg-Moerman (2017), we code the tone of news articles based on RavenPack's Composite Sentiment Scores (CSS).[20]

If the alternative interpretation holds, we would expect the coefficient on $News_{Negative\ t}$ to be significantly negative and that on $News_{Positive\ t}$ to be insignificant. In contrast, we find that not only negative news coverage but also positive news coverage has a negative impact on innovation. For example, the coefficients on $News_{Positive,t}$ and $News_{Negative,t}$ for $CitaPat_{t+2}$ are -0.081 and -0.187 (*t*-stats equal to -2.49 and -6.22) in Model (1) of Panel A, Table 6. Similar results are found for $PValue_{t+2}$ and $Patent_{t+2}$ in Models (2) and (3). These findings indeed indicate that news coverage with a positive tone exerts a significant impeding effect on corporate innovation, thus alleviating the concern that our results are driven by firms with poor fundamentals.

[Insert Table 6 Here]

Second, there are two potential concerns regarding our main specification that does not control for current innovation or a trend in innovation. First, our main results might be driven by the lifecycle effect, i.e., mature firms tend to gain greater media coverage and at the mean time have a lower level of innovation investments, which leads to less innovation outputs in the future. Moreover, the mean reversion effect of innovation activities predicts that firms with more current innovative project tend to attract a higher level of attention from the media, and these firms may have mean reversion to a lower level of innovation outputs.

[20] RavenPack's CSS range between 0 and 100, representing the news sentiment of a given story. CSS above (below) 50 are defined as positive (negative) news. The direction of the score is determined based on various sentiment analysis techniques (e.g., by looking at emotionally charged words and phrases and by matching stories typically rated by experts as having a short-term positive or negative impact on share prices).

Both concerns have been alleviated in our main analyses to some extent, because in our baseline models we control for firm age ($Age_{\ t}$) and current research and development expenses ($R\&D_{\ t}$), to take the lifecycle effect and the current level of long-term investment into account. To further mitigate this concern, in Panel B of Table 6, we control for either the current level of innovation or the change in innovation to illustrate the robustness of our main findings. Across all the Models from (1) to (6), we find that the coefficients on innovation outputs in year *t* ($CitaPat_t$, $PValue_t$, and $Patent_t$) and the changes in innovation outputs from year *t-1* to year *t* ($\Delta\ CitaPa_t$, $\Delta\ PValue_t$, and $\Delta\ Patent_t$) are positive and significant, suggesting the stickiness of innovation investment policy rather than a pattern of mean reversion. More importantly, the coefficients on $News_{\ t}$ are all negative and significant at the one percent level, indicating that the attenuation effect of news coverage on corporate innovation still holds when the potential lifecycle effect and mean reversion effects are controlled.

Finally, we use the change-in-change specification to revisit our main analyses, as an alternative approach to control for unobserved time invariant factors that influence both news coverage and innovation outputs, instead of controlling for firm fixed effects. Specifically, we regress the changes in innovation measures from year *t+1* to year *t+2* on the change in news coverage from year *t-1* to year *t*, and include the changes of control variables specified in Equation (1), as well as industry and year fixed effects. Results are reported in Panel C of Table 6. Consistent with our main findings, we find a negative effect of the change in news coverage ($\Delta\ News_{\ t}$) on the changes in patenting activities ($\Delta\ CitaPat_{t+2}$, $\Delta\ PValue_{t+2}$, and $\Delta\ Patent_{t+2}$). This suggests that any time invariant factors missed in our model are less likely to drive our headline findings regarding the impact of news coverage on innovation outputs, and thus mitigates the endogeneity concern linked to these unobserved factors.

4.3. Economic channels

Although the results so far show a negative effect of news coverage on innovation activities, this attenuation effect may be a net outcome in that the *spotlight-burning hypothesis* offsets the *spotlight-spurring hypothesis*. To further examine the two hypotheses, in this section, we investigate the underlying economic channels through which media coverage affects innovation.

4.3.1. Tests on economic channels based on news content

First, we decompose our overall news coverage measure (*$News_t$*) into several news sub-components based on news categories as defined in Section 3.2, which capture various media effects on innovation regarding the four economics channels.

According to the *spotlight-burning hypothesis*, we expect corporate innovation to be impeded by earnings-related news coverage ($News_{Earnings,t}$) because the media can place pressure on managers to meet short-term earnings target and forego long-term innovation projects (*market pressure channel*). We also expect the product and innovation related news coverage ($News_{Product,t}$) to exert a negative impact on innovation, due to the media effects of knowledge leakage and attentions attracted to competitors, which lead to large competitive threats and thus deter firms from making innovation investments (*innovation spillover channel*).

Based on the *spotlight-spurring hypothesis,* we predict that innovation outputs would increase with financing-related news coverage ($News_{Financing,t}$) because the media can help overcome financial constraints by improving firms' information environments and enhancing firms' credibility to investors (*financial constraint channel*). Moreover, we conjecture that governance-related news coverage ($News_{Governance,t}$) would be positively associated with innovation, because the monitoring role of the media can help resolve the agency problem of "lazy" or "greedy" managers and thus increase firms' investment in innovative projects (*external governance channel*).

Table 7 reports the results of the analyses on the sub-components of news coverage. We first regress innovation metrics on each individual news component separately, and then include all the four news sub-metrics to jointly test their impacts on innovation outcomes. In addition, across all the models, we include the measure of other news coverage ($News_{Other,t}$) to control for the potential confounding effects from other unspecified economic channels. Specifically, $News_{Other,t}$ is defined as the number of news articles that do not fall into any of the above four news categories.

Consistent with our expectation, the coefficients on $News_{Earnings,t}$ are all negative and significant at the one percent level from Models (1) to (3), which provides support for the economic channel in terms of placing short-term pressure on managers. In contrast, we find limited evidence on the economic channel regarding the knowledge leakage and attention attraction effects. For example, the coefficient on $News_{Product,t}$ is only significantly negative in Model (4) for $CitaPat_{t+2}$, while the coefficients are insignificant although negative for $PValue_{t+2}$ and $Patent_{t+2}$ in Models (5) and (6).

Regarding the *financial constraint channel*, Models (7) to (9) report the positive and significant impact of $News_{Financing\ t}$ on corporate innovation. This result is consistent with our prior that the media may alleviate firms' financial constraints by reducing information asymmetry, increasing managers' visibility and credibility, and enhancing investment in innovation. However, inconsistent with the *external governance channel*, we find that the coefficients on $News_{Governance,t}$ are significantly negative in Models (10) to (12). This implies that the governance role of media may discourage managers from making investments in innovative projects, possibly implying an excessive monitoring effect of the media.[21] Lastly, we find that the above results on news sub-components are qualitatively similar in Models (13) to (15) when they are included together in the regression analyses.

Overall, the results in Table 7 provide strong support for both the *market pressure channel* and the *financial constraint channel*.

[Insert Table 7 Here]

4.3.2. Tests on economic channels based on interaction variables

Second, to further investigate our economic channels, we conduct analyses by including the interaction terms between news coverage components and several channel-related factors in the following model:

$$\begin{aligned} Innovation_{t+2} = \alpha + \beta_{News} News_{Component,\,t} + \beta_{NewsCF} News_{Component,\,t} \times Channel\ Factor_t \\ + \beta_{CF}\ Channel\ Factor_t + \beta_{CV} Control\ Variables_t + \beta_{FE}\ Fixed\ Effects + \varepsilon, \end{aligned} \tag{4}$$

where $News_{Component,t}$ represents a sub-component of overall news coverage for each economic channel (i.e., $News_{Earnings,t}$, $News_{Product,t}$, $News_{Financing,t}$, and $News_{Governance,t}$), $Channel\ Factor_t$ is a list of variables associated with the economic channels. $Control\ Variables_t$ is the same set of control variables as in Equation (1), and *Fixed Effects* refers to firm and year fixed effects.

To test the *market pressure channel*, we follow Gaspar, Massa, and Matos (2005) to construct the channel factor for investor horizon, which is the weighted average of the total portfolio churn rates of institutional investors of firm *i* in the last quarter of year *t* (*Short*

[21] Prior literature on corporate governance suggests the potential excessive monitoring effects, for example, by shareholders (e.g., Burkart, Gromb, and Panunzi, 1997; Pagano and Röell, 1998) and by the board of directors (e.g., Almazan and Suarez, 2003; Adams and Ferreira, 2007).

$Horizon_t$). The higher the value of $Short\ Horizon_t$, the larger the proportion of short-term institutional investors who can pressure managers to forgo long-term investments in exchange for short-term performance. The results are reported in Models (1) to (3) of Table 8. Consistent with our expectation, we find that the negative effect of $News_{Earnings,t}$ on corporate innovation is stronger when a firm has a larger proportion of short-term institutional investors, i.e., negative and significant coefficients on $News_{Earnings\ t} \times Short\ Horizon_t$. This finding supports the *market pressure channel*.

Next, to test the *innovation spillover channel*, we use the product competition metric, $Fluidity_t$, developed by Hoberg, Phillips, and Prabhala (2014) to proxy for the potential competitive threat that can be amplified by media coverage. $Fluidity_t$ captures the changes in rival firms' products relative to a firm's own products, which are estimated based on the business descriptions from *10-K* annual filings for firm *i* in year *t*.[22] Using this measure, Hoberg, Phillips, and Prabhala (2014) find that firms associated with a higher level of *Fluidity* make fewer payouts and hold more cash because they face greater product market threats. From Models (4) to (6), we find the interactions between $News_{Product\ t}$ and $Fluidity_t$ are insignificant, even for $CitaPat_{t+2}$, of which the main $News_{Product\ t}$ effect is significantly negative. These results are not supportive in terms of the *innovation spillover channel*.

We adopt a popular proxy for firm-level financial constraints, $WWindex_t$, to test the *financial constraint channel*. Following Whited and Wu (2006), $WWindex_t$ is estimated as an index of the external finance constraints of firm *i* in year *t*. More specifically, this index is equal to $-0.091 \times CF - 0.062 \times DIVPOS + 0.021 \times TLTD - 0.044 \times LNTA + 0.102 \times ISG - 0.035 \times SG$, where *CF* is cash flows scaled by total assets, *DIVPOS* is an indicator equal to one if cash dividends are paid, *TLTD* is the long-term debt scaled by total assets, *LNTA* is the log value of total assets, *ISG* is industry sales growth based on the 3-digit SIC code, and *SG* is firm sales growth. A higher value of $WWindex_t$ suggests greater financial constraints faced by firm *i*. Models (7) to (9) show that the interaction terms between $News_{Financing\ t}$ and $WWindex_t$ are positive and significant for $CitaPat_{t+2}$ and $PValue_{t+2}$. This finding is consistent with our hypothesis relating to the *financial constraint channel* and indicates that the negative impact of media coverage on innovation is weakened for firms with financial constraints.

With regard to the *external governance channel*, we use a firm's internal governance system, $BIndependence_t$, as the channel factor. $BIndependence_t$ is defined as the proportion of

[22] Firms are required to describe and update information about their significant products by the U.S. Securities and Exchange Commission (SEC) in Item 101 of Regulation S-K. The data for *Fluidity* is obtained from Professor Gerard Hoberg's website.

independent directors on the board for firm *i* in year *t* based on BoardEx data. We regard this estimate as a proxy for firm's strong internal governance, because the prior literature documents that independent directors play a monitoring role in restricting management behavior (e.g., Weisbach, 1988; Hermalin and Weisbach, 1998). However, the negative main effect of $News_{Governance\ t}$ reported in Table 7 suggests the possible over-monitoring role of media in dampening innovation, in line with the literature on excessive monitoring (Burkart, Gromb, and Panunzi, 1997; Pagano and Röell, 1998; Almazan and Suarez, 2003; Adams and Ferreira, 2007). Thus, we may expect this excessive monitoring effect of media to be more pronounced for firms with stronger governance mechanisms in place. Accordingly, we report the results for the *external governance channel* in Models (10) to (12). The coefficients on the interactions between $News_{Governance\ t}$ and $BIndependence_t$ are negative and significant for $CitaPat_{t+2}$ and $PValue_{t+2}$. This implies that the potential excessive governance effect of media is stronger for firms with a larger proportion of independent directors, consistent with the findings in Table 7.

In summary, the results in Section 4.3 provide supportive evidence for the underlying economic channels through which media coverage affects innovation, and suggest that the main attenuation effect of news coverage on innovation is a net outcome when the *market pressure channel* dominates the *financial constraint channel*, and the *external governance channel* possibly exerts an over-monitoring effect.

[Insert Table 8 Here]

5. Additional tests

5.1. Does the quality of the innovator matter?

One could argue that the negative effect of media coverage on innovation is driven by the decrease in the innovation outputs of low-quality corporate innovators. In other words, the media may help the market effectively allocate resources from low-quality innovators to high-quality innovators.[23]

To test this possibility, following Clarke, Dass, and Patel (2015), we construct two measures of observed innovator quality in year *t* ($IQuality_{Citation,t}$ and $IQuality_{PValue,t}$). $IQuality_{Citation,t}$ is estimated based on the annual citation-to-patent ratio, and $IQuality_{PValue,t}$ is

[23] Clarke, Dass, and Patel (2015) show that the impeding effect of financial analysts on innovation, documented by He and Tian (2013), is subject to innovator quality.

the sum of patent value scaled by the market value of equity, both averaged for all the successful patents filed by a firm from year t-3 to t-1. The patent value is estimated based on the abnormal stock return after the issuance of a patent following KPSS (2017).

In Models (1) to (3) of Table 9, we include the interaction $News_t \times IQuality_{Citation,t}$ in the regressions. If the main impeding effect of news coverage is more pronounced for low-quality innovators, we would expect the coefficients on $News_t \times IQuality_{Citation,t}$ to be positive. However, we find that the coefficients are significantly negative, which suggests that the media's impeding effect is stronger for innovators with higher citation-to-patent ratios in prior years. For Models (4) through (6), we conduct the interaction analysis by testing $News_t \times IQuality_{PValue\ t}$ in regressions, and we find that the impeding effect of media coverage is also more pronounced for high-quality innovators who generate patents with greater values.

The evidence from the above analyses indicates that the main impeding effect of news coverage is not driven by a reduction in innovation from corporate innovators with poor productivity.

[Insert Table 9 Here]

5.2. News coverage and alternative growth measures

Our main findings are based on patenting activities, which may not well capture growth prospects for certain types of firms, especially for those with limited demand for patenting. In this section, we examine the impact of news coverage on several alternative growth metrics to further understand the real effects of the media within the framework of the Gordon growth model.

To identify the candidates for alternative growth proxies, we conjecture three steps in a loose timeline through which the media can shape firms' growth prospects: 1) altering investment decisions such as research and development expenses (R&Ds) in year t, 2) influencing innovation outputs in year $t+2$, and 3) changing the growth of cash flows in year $t+3$. Given that the second stage has been examined in our main analyses, we close the loop by estimating the alternative growth measures according to the first and third steps. To do so, we choose three firm growth metrics, $Growth_{CFO,t+3}$, $Growth_{SG\&A,t}$, and $Growth_{R\&D,t}$ to construct a common factor for a firm's growth prospect, $Growth_{Overall}$ (Guay, 1999). Specifically, we estimate $Growth_{CFO\ t+3}$ as the growth rate of cash flows from operation adjusted by the industry median in year $t+3$, which is less subject to managerial accounting choices. Following Roychowdhury (2006), we define $Growth_{SG\&A,t}$ as the discretionary total selling, general, and administrative expenses scaled by total assets based on each two-digit SIC industry-year group in year *t*. Similarly, we calculate the discretionary research and development expenses scaled by total assets, $Growth_{R\&D,t}$, as the proxy for the inputs of innovative projects in year *t*.

We regress these growth metrics on news coverage and present the results in Table 10. In Panel A, Model (1) shows that the coefficients on $News_t$ are negative and significant for the compounded growth measure, $Growth_{Overall}$. Models (2) to (4) indicate that the attenuation news effect on growth prospect holds for each of the three individual growth proxies, $Growth_{CFO,t+3}$, $Growth_{SG\&A,t}$, and $Growth_{R\&D,t}$. In Panel B, we use the same instrument variable, $TravelTime_t$, to conduct the two-stage instrument variable analysis for these alternative growth metrics. Consistent with the OLS regression, we find that the predicted news coverage, $News_{Predict,t}$, has negative and significant impacts on $Growth_{Overall}$, $Growth_{CFO,t+3}$, and $Growth_{R\&D,t}$, with the only exception that the coefficient on $News_{Predict,t}$ is insignificant although negative for $Growth_{SG\&A,t}$.

In summary, we confirm that not only patenting activities but also a firm's general growth prospects are attenuated by media coverage. This evidence is in support of the generality of our main findings.

[Insert Table 10 Here]

5.3. Robustness tests

In this section, we analyze whether the impact of media coverage on corporate innovation activities holds against different measures of innovation outputs and news coverage, alternative sample selections, and various clustering techniques. We also examine how the media effect varies according to news article characteristics. Last, we conduct our analysis using the alternative data source of news coverage. All these results are reported in the Internet Appendix (IA). The definitions of new variables constructed for these tests are detailed in Table IA 1.

5.3.1. Alternative measures of innovation outcome and news coverage

In this sub-section, we test the robustness of our main results using different measures of corporate innovation and news coverage. First, we examine whether our results hold in the analysis when predicting three-year ahead innovation outputs ($Innovation_{t+3}$). In Models (1) to (3) of Table IA 2, we find that the use of a two-year window versus a three-year window between news coverage and innovation outcomes does not drive our baseline findings.

Second, we use the count of citations for patents granted in year *t+2* ($Citation_{t+2}$), the sum of patent value for patents granted in year *t*+2 ($PValue_{Raw,\ t+2}$), and the average patent value for patents granted in year *t+2* ($PValue_{Adj,\ t+2}$) as the alternative innovation metrics. The patent value is again estimated based on the stock return following the patent grant date (KPSS, 2017). Accordingly, the results presented in Models (4) to (6) of Table IA 2 are consistent with our main findings that news coverage exerts a negative and significant impact on innovation outcomes.

Third, in Table IA 3, we deflate news coverage and innovation outputs using different firm size proxies. In particular, corporate innovation and news coverage measures are scaled by the market value of equity in Models (1) to (3), by the book value of total assets in Models (4) to (6), and by the number of employees in Models (6) to (9). The results in Table IA 3 show negative and significant coefficients on news coverage regardless of which scalar of firm size is used, indicating that the attenuation effect of media coverage on innovation holds after the scaling effect is considered.

5.3.2. Alternative sample selections and clustering techniques

We further address the sample selection concern in Table IA 4. We drop observations with $News_t$ = 0 in Models (1) to (3) to check whether the inclusion of zero-news-coverage firm-years drives our main findings. In Models (4) to (6), we focus on the sub-sample period from 2000 to 2007 to further alleviate the concern on the truncation bias of patent information. We find similar results based on these selection criteria. Furthermore, in Table IA 5, we cluster standard errors by industry (state) instead of by firm in Models (1) to (3) (Models 4 to 6) to control for cross-sectional industry-level (state-level) dependence. We again find that the negative impact of news coverage on corporate innovation is statistically significant.

5.3.3. Additional tests on news characteristics

In this section, we explore whether the media effect on innovation varies according to the characteristics of news articles.

The media can play two important roles as information intermediaries in capital markets. On the one hand, in terms of the information exploration function, the media can influence corporate decisions by providing new information to the market based on original investigations and analyses (Miller, 2006; Dyck, Volchkova, and Zingales, 2008). On the other hand, in the news dissemination function, the media affects corporate policies by disseminating news about corporate events to the public (Liu and McConnell, 2013; Dai, Parwada, and Zhang, 2015). We investigate how these two functions affect managers' decisions regarding innovation activities.

Specifically, we decompose $News_t$ into two news coverage metrics. $News_{Repeated,t}$ ($News_{Original,t}$) is the number of repeated (original) news articles for firm i in year t. News articles are grouped into repeated or original news articles based on RavenPack's Event Novelty Scores (ENS). For example, the first news article reporting an event receives a novelty score of 100. Subsequent news articles reporting the same event receive scores of less than 100. We classify news articles with ENS=100 as original news articles and those with ENS<100 as repeated news articles. We present the results in Models (1) to (3) of Table IA 6. In general, the coefficients on both $News_{Repeated,t}$ and $News_{Original,t}$ are negative and significant, which provide evidence for both the news dissemination and information exploration functions of the media.

Next, we examine whether corporate initiated press releases matter for the media effect, which are excluded from the estimation of our main news coverage measure, $News_t$. From Models (4) to (6), we include the number of press releases initiated by firms themselves ($News_{Press\ Release,t}$) in the regression analyses. We find that the coefficients on $News_t$ after controlling for $News_{Press\ Release,t}$ are significantly negative, while $News_{PressRelease,t}$ does not consistently exert an impeding effect. This finding suggests that the news coverage effect conducted by external reporters on managers' innovation decisions is not driven or dominated by managers' voluntary information disclosures through press releases.

5.3.4. Alternative data source of news coverage

One might be concerned about the breadth of news coverage measured based on RavenPack, because RavenPack is sourced mainly from *Dow Jones Newswires*, *The Wall Street Journal*, and *Barron's* prior to 2007 (i.e., based on the Dow Jones Edition). If young and small firms are largely covered by local and regional papers, RavenPack may not sufficiently capture news articles on these firms potentially with large growth opportunities. This is less of a concern for the years from 2007 to 2010, because in 2007 RavenPack started to be sourced from the Web Edition data that covers a broader set of information sources including, for example, local news articles.

To address this concern, we use an alternative news data, the Thomson Reuters News Archive (TRNA) database (Li, Ramesh, Shen, and Wu, 2015). TRNA collects news articles from *Reuters News* based on the sources such as *Business Wire* and *PR Newswire*. We obtain the TRNA data from Thomson Reuters in a limited sample period between 2003 and 2010. $News_{TRNA,\,t}$ is estimated as the number of news articles from TRNA for firm *i* in year *t*. The correlation coefficient between $News_{TRNA\ t}$ and $News_{t}$ (based on RavenPack) is 66.49% in the overlapping period 2003-2010. This suggests that the two news data sources have a similar but not identical coverage of firms. In Table IA 7, we regress $Innovation_{t+2}$ on $News_{TRNA,\,t}$ from Models (1) to (3) and find similar results to those based on RavenPack. The coefficients on $News_{TRNA,\,t}$ are negative and significant for $CitaPat_{t+2}$ and $PValue_{t+2}$, though insignificant for $Patent_{t+2}$.

Given that RavenPack and TRNA are sourced from different newswires, we also merge RavenPack with TRNA to construct the two combined measures of news coverage. First, we define $News_{TRNA+RavenPack,\,1,\,t}$ as $News_{t}$ in year *t* over the period from 2003 to 2010, which is replaced by $News_{TRNA\ t}$ if $News_{t}$ is zero. The results reported in Models (4) to (6) show that the coefficients on $News_{TRNA+RavenPack,\,1,\,t}$ are both negative and significant at the one percent level. Second, we estimate $News_{TRNA+RavenPack,\,2,\,t}$ as the sum of $News_{t}$ and $News_{TRNA,\,t}$ for firm *i* in year *t* from 2000 to 2010. For the years between 2000 and 2002, we denote the value of $News_{TRNA+RavenPack,\,2,\,t}$ the same as $News_{t}$. Across Models (7) to (9), we find that the coefficients on $News_{TRNA+RavenPack,2,\,t}$ remain significantly negative. Taken together, we show that our prior main findings hold using this alternative data source of media coverage, alleviating the concern regarding the breadth of RavenPack data.

6. Conclusion

Theoretically, a firm’s ultimate goal is to maximize shareholders’ wealth, which is determined by both the risk and the growth prospect of future cash flows. Therefore, it is important to understand how media coverage affects firms’ long-term growth through innovation. In this study, we examine the effect of media coverage on corporate innovation based on two hypotheses: the *spotlight-burning hypothesis* and the *spotlight-spurring hypothesis*.

We use a comprehensive dataset of corporate news coverage and innovation outputs for the period from 2000 to 2012 to perform our analyses. Our baseline finding is consistent with the *spotlight-burning hypothesis* that media coverage exerts a negative effect on firm innovation. Moreover, we find support for two economic mechanisms that underlie the effect of news coverage on innovation, namely, news coverage imposes excessive market pressure on managers and overcomes financial constraints. Our work thus sheds some light on how the media affects corporate long-term policies and provides avenues for further research on the real effects of news coverage.

Appendix

Variable definitions and data sources.

This appendix presents variable definitions and data sources.

Variable	Definition
Innovation outcome variables	
CitaPat	Average number of citations per patent for patents granted in one year based on the data provided by *KPSS* (Kogan, Papanikolaou, Seru, and Stoffman, 2017) from *Google Patents*, which is also complemented by the data collected from *Google United States Patent* and *Trademark Office (USPTO) Bulk Downloads*. The number of citations per patent is adjusted for truncation, where the raw value is divided by the sample annual mean (Hall, Jaffe, and Trajtenberg, 2001). Log value of *CitaPat* is taken in the regression analysis.
PValue	Sum of patent values scaled by market value of equity for patents granted in one year based on the data provided by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads*, as well as *Compustat Annual*. The patent value is estimated based on the stock return following patent grant date using the approach from *KPSS* (2017). Log value of *PValue* is taken in the regression analysis, and *PValue* reported in Table 2 is multiplied by 100 for exposition purpose.
Patent	Number of patents filed and eventually granted in one year based on the data extracted by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads.* Log value of *Patent* is taken in the regression analysis.
News coverage variables	
News	Number of news articles in one year based on *RavenPack* and divided by 100 in regression analysis.
$News_{Predicted}$	Predicted number of news articles released in one year, which is estimated in an instrumental variable approach based on *RavenPack*.
$News_{High}$	Indicator equal to one if the number of news articles is above the sample median in one year based on *RavenPack*.
$News_{Positive}$	Number of positive news articles in one year based on *RavenPack*.
$News_{Negative}$	Number of negative news articles in one year based on *RavenPack*.
$News_{Earnings}$	Number of earnings related news articles in one year based on *RavenPack*.
$News_{Product}$	Number of product related news articles in one year based on *RavenPack*.
$News_{Financing}$	Number of financing related news articles in one year based on *RavenPack*.
$News_{Governance}$	Number of governance related news articles in one year based on *RavenPack*.
$News_{Other}$	Number of all other news articles in one year based on *RavenPack*.
Firm-level control variables	
Assets	*Book value of total assets* in billions (*US dollars*) based on *Compustat Annual*. Log value of (*1 + Assets × 1000*) is taken in the regression analysis.
R&D	*Research and development expenses* / *Assets* in one year based on *Compustat Annual*.
Age	Firm age in years based on *Compustat Annual*. Log value of *Age* is taken in the regression analysis.
ROA	*Net income* / *Assets* in one year based on *Compustat Annual*.
PPE	*Property, plant and equipment* / *Assets* based on *Compustat Annual*.
Leverage	(*Debt in current liabilities* + *Long-term debt*) / *Assets* based on *Compustat Annual*.
Capex	*Capital expenditures* / *Assets* in one year based on *Compustat Annual.*
TobinQ	(*Assets – Book value of equity + Number of common shares × Year-end share price*) / *Assets* based on *Compustat Annual*.
KZIndex	Kaplan and Zingales index divided by 100 based on *Compustat Annual*. See Kaplan and Zingales (1997) for details.

Appendix - Continued

Variable	Definition
HIndex	Herfindahl index of four-digit standard industrial classification (*SIC*) using *Sales* information based on *Compustat Annual*.
InstOwn	Shares owned by institutions scaled by total shares outstanding based on *Thomson Reuters Institutional (13f) Holdings*.
Analyst	Number of analysts issuing annual *EPS* forecasts based on *I/B/E/S Summary Statistics*. Log value of (*1 + Analyst*) is taken in the regression analysis.
Spread	Average daily bid-ask spread estimated in one year based on *CRSP*. See Corwin and Schultz (2012) for details.
Other variables	
$R\&D_{Existence}$	Indicator equal to one if the R&D expense is non-missing for at least one year throughout the sample period and equal to zero otherwise, based on *Compustat Annual*.
$Industry_{Manufacture}$	Indicator equal to one if a firm is incorporated in the manufacture industry and equal to zero otherwise, based on *Compustat Annual*.
$Patent_{Existence}$	Indicator equal to one if the patenting information is non-missing for at least one year throughout the sample period and equal to zero otherwise, based on the data provided by *KPSS* (2017) and also the data collected from *Google USPTO Bulk Downloads*.
TravelTime	Median value of the number of minutes for trips between headquarters of a firm and Dow Jones offices in one year, estimated based on the flight information from the *U.S. Department of Transportation T-100 Segment* data.
$Post_{NewsPlus}$	Indicator equal to one if the calendar year is between 2003 and 2005 and equal to zero if it is between 2000 and 2002. These are the event windows around the launch of Dow Jones NewsPlus service provided by Dow Jones, which provides the subscribers of Dow Jones News Service with simple web navigation techniques.
ShortHorizon	Weighted average churn rate of all the institutional investors of a firm in the fourth quarter of one year estimated based on *Thomson Reuters Institutional (13f) Holdings*. See Gaspar, Massa and Matos (2005) for details.
Fluidity	Text-based measure of competitive threats faced by a firm in the product market that captures changes in rival firms' products relative to the firm estimated using *10-Ks* in one year provided by Hoberg, Phillips, and Prabhala (2014).
BIndependence	Proportion of independent directors on the board of a firm in one year based on *BoardEx*.
WWIndex	Index of external finance constraints of a firm estimated in one year based on *Compustat Annual*, which is transformed to decile-ranking metric. See Whited and Wu (2006) for details.
$IQuality_{Citation}$	Annual truncation adjusted citation-to-patent ratio averaged over previous three years as a proxy for innovator quality, estimated based on the data provided by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads*. Number of citations per patent is adjusted for truncation, where the raw value is divided by the sample annual mean (Hall, Jaffe, and Trajtenberg, 2001). Log value of $IQuality_{Citation}$ is taken in the regression analysis.
$IQuality_{PValue}$	Sum of patent value scaled by market value of equity averaged over previous three years as a proxy for innovator quality, estimated based on the data provided by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads*. The patent value is estimated based on the stock return following patent grant date using the approach from *KPSS* (2017). Log value of $IQuality_{PValue}$ is taken in the regression analysis.
$Growth_{Overall}$	Principal component of $Growth_{CFO\ t+3}$, $Growth_{SG\&A\ t}$, and $Growth_{R\&D\ t}$ based on *Compustat Annual*.

Appendix - Continued

Variable	Definition
$Growth_{CFO}$	Growth rate of cash flow from operation adjusted by industry median in one year based on *Compustat Annual*.
$Growth_{SG\&A}$	Discretionary selling, general and administrative expenses scaled by total assets in one year, estimated based on *Compustat Annual* using Roychowdhury's (2006) approach which estimates discretionary total expenses.
$Growth_{R\&D}$	Discretionary research and development expenses scaled by total assets in one year, estimated based on *Compustat Annual* using Roychowdhury's (2006) approach which estimates discretionary total expenses.

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Figure 1

Distribution of news categories

This figure presents the distribution of news categories for *News* $_{Earnings}$, *News* $_{Product}$, *News* $_{Governance}$, *News* $_{Financing}$, and other types of news, *News* $_{Other}$ in RavenPack database.

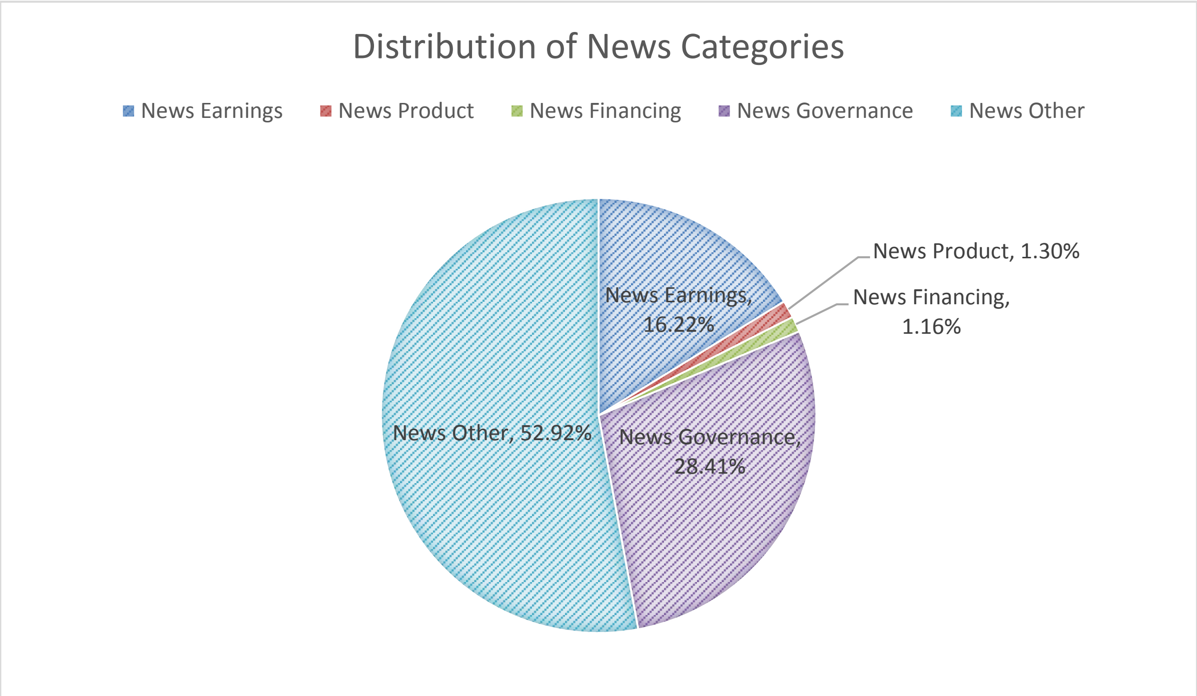

Figure 2

Distributions of news coverage and patent grant by firm size

This figure presents the mean values of two metrics, news coverage in year *t* (*$News_t$*) and number of patents granted in year *t+2* (*$Patent_{t+2}$*) in sub-samples divided by firm size in terms of total assets (*$Assets_t$*).

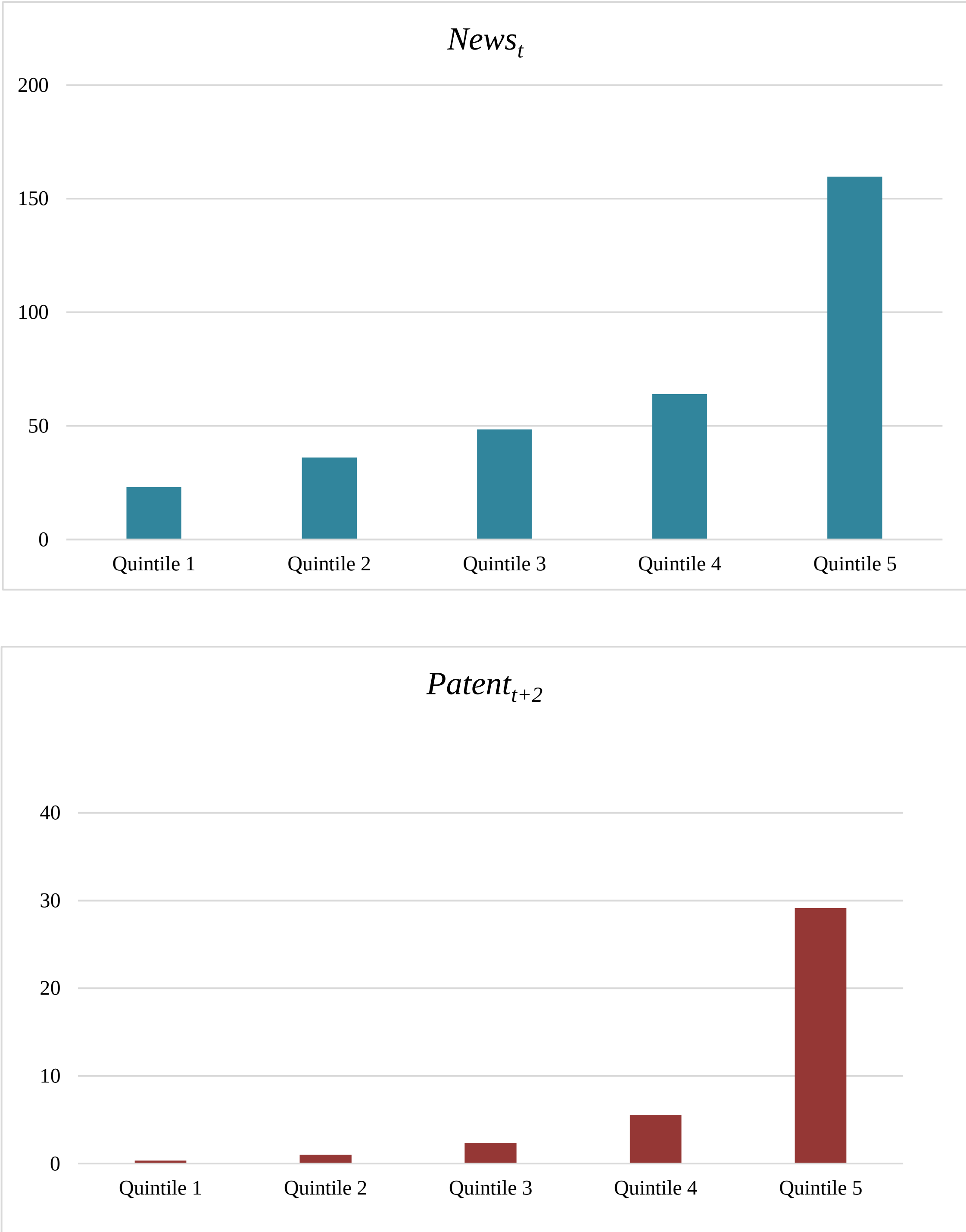

Figure 3

Illustration of the calculation of the instrumental variable: *TravelTime*.

This figure illustrates the calculation of our instrumental variable *TravelTime* by using ADC Telecommunication Inc. and Dow Jones' Boston office as an example.

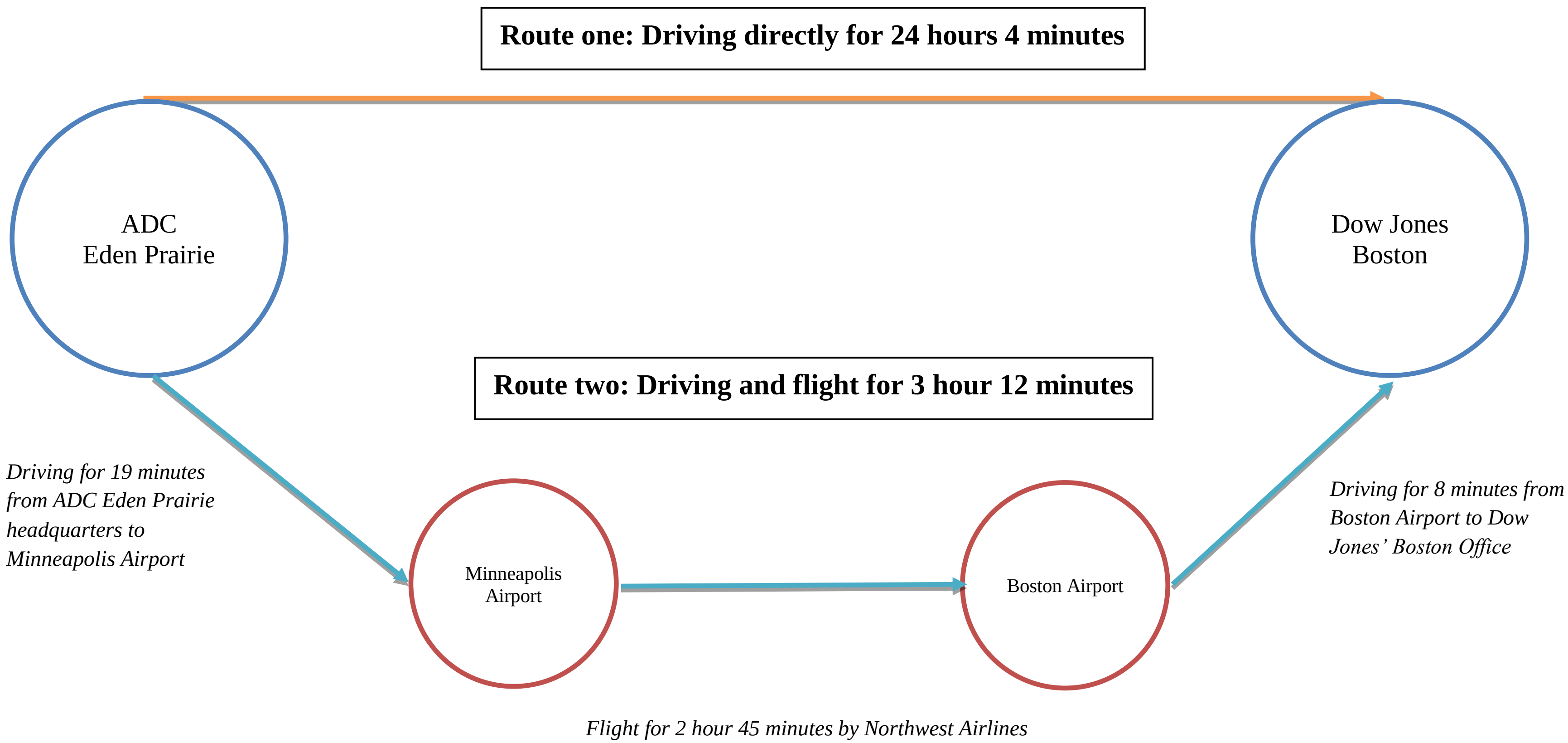

Figure 4

Snapshots from the illustration of NewsPlus on Dow Jones website.

This figure presents the snapshots regarding the key features of *NewsPlus* from the illustration from Dow Jones website (https://www.dowjones.com/products/newswires/newsplus).

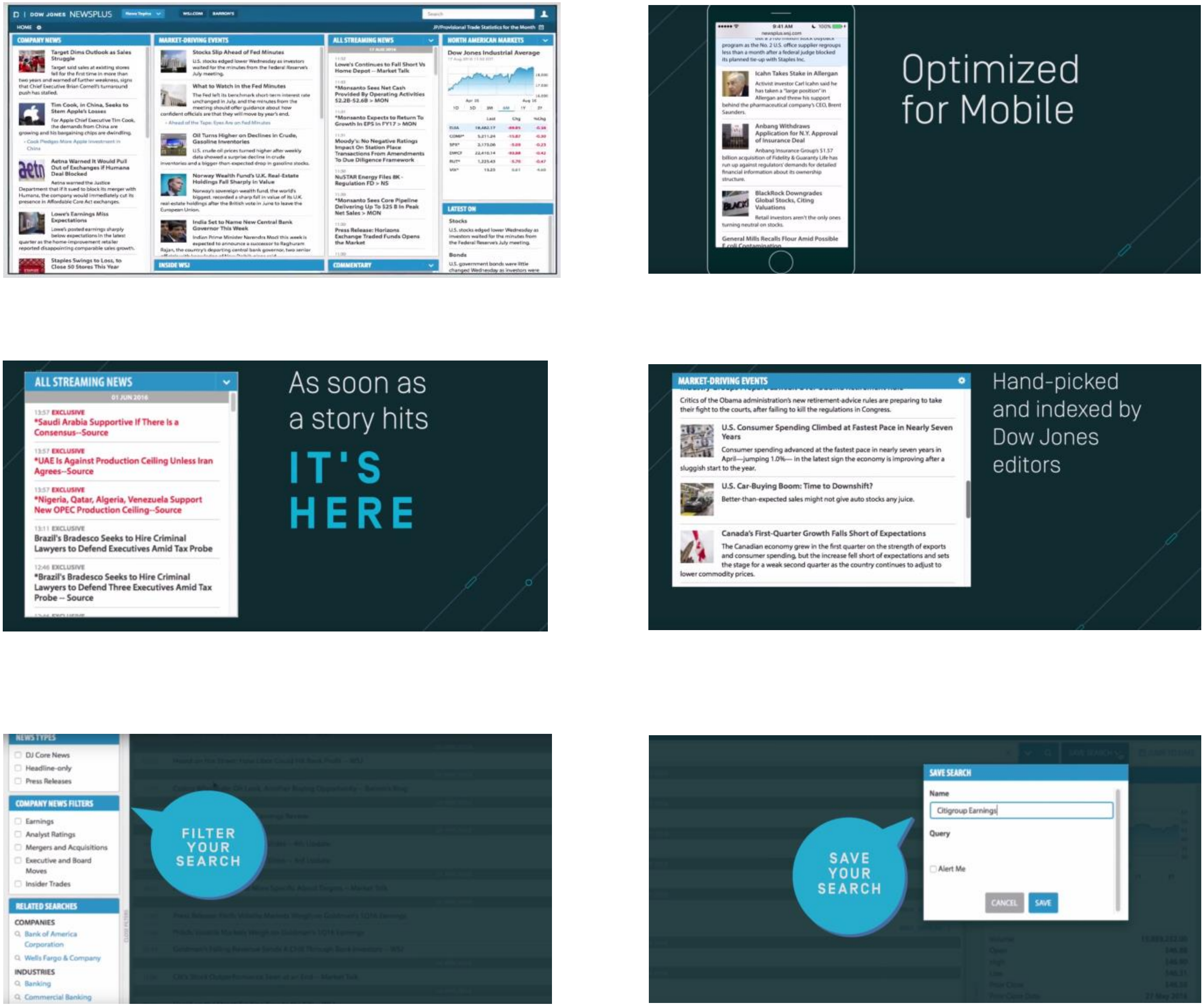

Table 1

Sample selection

This table presents the sample selection procedure. We start with a comprehensive dataset of corporate news coverage and innovation outputs for the period from 2000 to 2012 based on *Compustat* and *RavenPack*. The sample in our main analysis comprises 34,642 firm-year observations with news coverage variables estimated in year *t* from 2000 to 2010, and with innovation outcome variables estimated in year *t+2* from 2002 to 2012. In supplementary analyses, the sample period varies across different specifications. Variable definitions are detailed in the Appendix.

Step	**Selection Criteria**	**Observations**
1.	Firm-year observations from news-release in a combined sample based on *Compustat* and *RavenPack*.	52,955
2.	- Less observations with two-digit SIC codes between 4900 and 4999, or between 6000 and 6999.	39,439
3.	- Less observations with missing values of control variables estimated based on *Compustat*, such as *Assets*, *PPE*, *Leverage*, *Capex*, and *KZindex*.	37,064
4.	- Less observations with missing value of *Spread* estimated based on *CRSP*.	36,782
5.	- Less observations with missing value of *Travel Time* estimated based on the information of firm's headquarters location from *Compustat*.	34,642

Table 2

Summary statistics

This table presents the summary statistics of the variables in our main analysis for the mean, median, standard deviation (*STD*), and decile (90% and 10%) distributions of the variables. The full panel sample comprises 36,782 firm-year observations for news coverage variable from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Variable definitions are detailed in the Appendix.

	Mean	*STD*	*10%*	*Median*	*90%*
$CitaPat_{t+2}$	1.424	4.712	0.000	0.000	4.005
$PValue_{t+2}$	1.375	3.759	0.000	0.000	4.511
$Patent_{t+2}$	7.674	35.879	0.000	0.000	7.000
$News_t$	66.258	99.010	6.000	39.000	140.000
$Assets_t$	2.632	9.671	0.025	0.307	4.713
$R\&D_t$	0.061	0.117	0.000	0.005	0.179
Age_t	18.806	14.020	6.000	14.000	42.000
ROA_t	-0.054	0.269	-0.332	0.029	0.122
PPE_t	0.249	0.232	0.031	0.168	0.629
$Leverage_t$	0.181	0.186	0.000	0.136	0.452
$Capex_t$	0.053	0.061	0.007	0.032	0.124
$TobinQ_t$	2.103	1.693	0.899	1.545	3.875
$KZIndex_t$	-0.125	0.508	-0.234	-0.014	0.019
$HIndex_t$	0.227	0.177	0.067	0.173	0.466
$InstOwn_t$	0.429	0.357	0.000	0.417	0.928
$Analyst_t$	5.429	6.271	0.000	3.000	14.000
$Spread_t$	0.021	0.012	0.009	0.018	0.037

Table 3

News coverage and innovation outcomes

This table presents regressions of corporate innovation outcome variables on news coverage, including other control variables and unreported firm- and year-fixed effects (*FY*). The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the sum of patent values scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. The full panel sample comprises 36,782 firm-year observations for news coverage variable from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Panel A examines the full sample, while Panel B investigates the sub-samples of firms with more patenting activities. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

Panel A: Full Sample

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3
$News_t$	**-0.062**	**-0.127**	**-0.078**
	(-4.71)	**(-8.11)**	**(-3.35)**
$Assets_t$	0.085	0.113	0.134
	(4.88)	(7.70)	(7.81)
$R\&D_t$	-0.181	-0.276	-0.186
	(-1.37)	(-2.62)	(-1.69)
Age_t	0.036	0.175	-0.270
	(0.59)	(3.06)	(-4.47)
ROA_t	-0.060	-0.059	-0.040
	(-1.69)	(-2.40)	(-1.50)
PPE_t	0.128	0.108	0.096
	(1.61)	(1.53)	(1.20)
$Leverage_t$	-0.185	-0.146	-0.163
	(-3.13)	(-2.73)	(-2.69)
$Capex_t$	0.038	0.121	0.146
	(0.35)	(1.45)	(1.70)
$TobinQ_t$	0.042	0.042	0.027
	(7.94)	(10.17)	(5.93)
$KZIndex_t$	-0.034	-0.022	-0.012
	(-2.60)	(-2.25)	(-1.32)
$HIndex_t$	0.740	1.022	0.817
	(2.40)	(3.56)	(2.77)
$HIndex^2_t$	-0.670	-0.940	-0.900
	(-2.29)	(-3.21)	(-2.96)
$InstOwn_t$	-0.068	-0.037	-0.033
	(-1.66)	(-1.00)	(-0.77)
$Analyst_t$	0.010	0.022	-0.005
	(0.78)	(1.89)	(-0.39)
$Spread_t$	6.266	5.909	0.220
	(8.14)	(9.61)	(0.34)
Fixed Effects	FY	FY	FY
Observations	36,782	36,782	36,782
R^2_{Adj}	45.37%	55.91%	74.83%

Panel B: Sub-Sample

Variable	$R\&D_t > 0$			$R\&D_{Existence} = 1$			$Industry_{Manufacture} = 1$			$Patent_{Existence} = 1$		
	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
$News_t$	**-0.038**	**-0.152**	**-0.089**	**-0.049**	**-0.156**	**-0.102**	**-0.078**	**-0.188**	**-0.101**	**-0.035**	**-0.123**	**-0.085**
	(-2.34)	**(-7.85)**	**(-2.91)**	**(-3.06)**	**(-8.09)**	**(-3.21)**	**(-4.81)**	**(-8.17)**	**(-3.09)**	**(-2.38)**	**(-7.00)**	**(-2.90)**
$Assets_t$	-0.012	0.072	0.168	0.010	0.078	0.162	0.023	0.104	0.171	-0.004	0.068	0.173
	(-0.44)	(2.97)	(5.17)	(0.38)	(3.53)	(5.70)	(0.81)	(4.07)	(5.24)	(-0.13)	(2.98)	(5.72)
$R\&D_t$	-0.074	-0.082	-0.008	-0.081	-0.116	-0.045	-0.205	-0.231	-0.168	-0.165	-0.200	-0.074
	(-0.52)	(-0.73)	(-0.06)	(-0.58)	(-1.07)	(-0.38)	(-1.34)	(-1.90)	(-1.25)	(-1.07)	(-1.66)	(-0.54)
Age_t	-0.019	0.301	-0.441	0.030	0.309	-0.385	-0.146	-0.008	-0.654	-0.336	-0.044	-0.580
	(-0.20)	(3.27)	(-4.08)	(0.33)	(3.58)	(-3.88)	(-1.49)	(-0.09)	(-5.98)	(-3.65)	(-0.52)	(-5.39)
ROA_t	0.007	-0.006	0.002	0.008	-0.016	-0.006	-0.056	-0.093	-0.085	0.012	0.014	-0.007
	(0.14)	(-0.19)	(0.04)	(0.19)	(-0.51)	(-0.18)	(-1.10)	(-2.32)	(-1.87)	(0.22)	(0.40)	(-0.16)
PPE_t	-0.288	-0.361	0.062	-0.238	-0.310	0.044	-0.183	-0.202	0.106	-0.060	-0.103	0.213
	(-1.72)	(-2.48)	(0.35)	(-1.54)	(-2.33)	(0.27)	(-1.18)	(-1.50)	(0.69)	(-0.38)	(-0.76)	(1.27)
$Leverage_t$	-0.154	-0.141	-0.157	-0.181	-0.163	-0.173	-0.227	-0.247	-0.278	-0.173	-0.156	-0.172
	(-1.70)	(-1.72)	(-1.48)	(-2.11)	(-2.11)	(-1.78)	(-2.58)	(-2.98)	(-2.80)	(-1.94)	(-1.96)	(-1.70)
$Capex_t$	0.305	0.552	-0.061	0.322	0.523	0.016	0.479	0.661	0.082	0.191	0.420	0.100
	(1.11)	(2.73)	(-0.26)	(1.25)	(2.79)	(0.08)	(1.90)	(3.41)	(0.39)	(0.73)	(2.20)	(0.47)
$TobinQ_t$	0.019	0.025	0.021	0.024	0.029	0.024	0.030	0.039	0.026	0.024	0.032	0.024
	(2.81)	(5.07)	(3.63)	(3.82)	(6.20)	(4.31)	(4.38)	(7.07)	(4.30)	(3.50)	(6.16)	(3.77)
$KZIndex_t$	-0.037	-0.025	-0.012	-0.036	-0.024	-0.011	-0.022	-0.013	-0.006	-0.040	-0.026	-0.011
	(-2.16)	(-2.00)	(-0.92)	(-2.22)	(-1.98)	(-0.89)	(-1.24)	(-0.91)	(-0.42)	(-2.01)	(-1.86)	(-0.74)
$HIndex_t$	0.399	1.216	1.312	0.413	1.129	1.027	1.208	1.569	1.114	0.238	1.059	0.950
	(0.75)	(2.38)	(2.22)	(0.84)	(2.44)	(1.96)	(2.60)	(3.43)	(2.23)	(0.49)	(2.32)	(1.81)
$HIndex^2_t$	-0.492	-1.195	-1.482	-0.469	-1.055	-1.170	-0.884	-1.149	-1.074	-0.302	-1.066	-1.177
	(-0.98)	(-2.24)	(-2.48)	(-1.04)	(-2.26)	(-2.27)	(-2.10)	(-2.58)	(-2.25)	(-0.66)	(-2.30)	(-2.24)
$InstOwn_t$	-0.113	-0.073	-0.072	-0.120	-0.074	-0.076	-0.094	-0.117	-0.042	-0.058	-0.040	-0.061
	(-1.61)	(-1.14)	(-0.89)	(-1.84)	(-1.24)	(-1.04)	(-1.40)	(-1.77)	(-0.51)	(-0.91)	(-0.68)	(-0.81)
$Analyst_t$	0.039	0.056	0.005	0.035	0.050	0.001	0.030	0.054	0.003	0.032	0.040	-0.003
	(1.88)	(3.11)	(0.22)	(1.80)	(2.94)	(0.04)	(1.40)	(2.78)	(0.12)	(1.59)	(2.31)	(-0.14)
$Spread_t$	3.549	3.273	-2.302	3.995	3.716	-2.060	5.485	7.260	-0.165	6.251	6.137	-1.862
	(2.80)	(3.23)	(-2.04)	(3.40)	(3.96)	(-2.02)	(4.58)	(7.17)	(-0.15)	(4.84)	(5.96)	(-1.59)
Fixed	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY
Observations	19,619	19,619	19,619	21,131	21,131	21,131	18,904	18,904	18,904	20,655	20,655	20,655
R^2_{Adj}	49.38%	61.33%	74.53%	48.62%	60.35%	74.48%	50.01%	60.18%	74.55%	47.82%	59.70%	73.33%

Table 4

Endogeneity tests using the instrumental variable analysis

This table presents endogeneity tests using instrumental variable analysis. In the first stage, *News*, the number of news articles is regressed on the instrumental variable *Travel Time* in year *t*, including other control variables and unreported firm- and industry-fixed effects (*IY*). *Travel Time* is the median value of the number of minutes for trips taken between the headquarters of the firm and Dow Jones offices in year *t*. In the second stage, corporate innovation outcome variables estimated in year *t+2* are regressed on the predicted news coverage ($News_{Predicted}$) estimated in year *t* from the first stage. The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the sum of patent values scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. Panel A describes the cities of Dow Jones offices, the airport cities closest to Dow Jones offices, the average travel time in minutes between headquarters and Dow Jones offices, and the distribution of travel method in percentage with regard to Dow Jones office. Panel B presents the two-stage regression results. The panel sample comprises 34,642 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012, with the available information of firm headquarters location from Compustat. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

Panel A: Travel Time and Travel Method between Firm's Headquarters and Dow Jones Offices

Dow Jones Office	Airport	Travel Time	By Car	By Direct Flight	By Transfer Flight	By Flight
Boston	Boston	233.58	6.39%	6.65%	86.96%	93.61%
Chicago	Chicago	201.40	4.32%	11.14%	84.54%	95.68%
Minneapolis	Minneapolis	217.69	3.00%	11.99%	85.01%	97.00%
New York	New York	229.19	13.08%	5.83%	81.09%	86.92%
Princeton	Philadelphia	270.49	15.55%	4.50%	79.95%	84.45%
San Francisco	San Francisco	313.14	7.13%	7.39%	85.48%	92.87%
Waltham	Boston	249.86	6.75%	6.58%	86.67%	93.25%
Washington	Washington	218.35	3.96%	8.55%	87.50%	96.04%

Table 4 - Continued

Panel B: Two-Stage Instrumental Variable Regression

	Stage 1	Stage 2	Stage 2	Stage 2
	News $_t$	*CitaPat* $_{t+2}$	*PValue* $_{t+2}$	*Patent* $_{t+2}$
Variable	M1	M2	M3	M4
News $_{Predicted\ t}$		**-1.159**	**-0.825**	**-1.339**
		(-5.97)	**(-4.63)**	**(-3.54)**
TravelTime $_t$	**-0.030**			
	(-2.96)			
Assets $_t$	0.307	0.443	0.360	0.702
	(15.11)	(7.44)	(6.59)	(5.98)
R&D $_t$	0.255	0.844	0.874	1.292
	(3.36)	(9.49)	(10.77)	(8.50)
Age $_t$	0.185	0.219	0.185	0.449
	(9.88)	(5.66)	(5.17)	(6.06)
ROA $_t$	-0.085	0.032	0.058	0.061
	(-3.62)	(0.95)	(2.19)	(1.30)
PPE $_t$	-0.187	-0.328	-0.267	-0.615
	(-3.03)	(-5.64)	(-4.82)	(-5.29)
Leverage $_t$	-0.337	-0.597	-0.421	-0.833
	(-5.36)	(-8.08)	(-6.20)	(-5.60)
Capex $_t$	0.434	0.666	0.603	1.397
	(3.22)	(4.97)	(5.11)	(6.02)
TobinQ $_t$	0.070	0.123	0.093	0.163
	(9.89)	(8.75)	(7.16)	(5.93)
KZIndex $_t$	-0.004	-0.004	-0.003	0.012
	(-0.35)	(-0.44)	(-0.36)	(1.06)
HIndex $_t$	-0.138	-0.268	-0.189	-0.673
	(-0.71)	(-1.85)	(-1.46)	(-2.32)
HIndex $^2{}_t$	0.270	0.417	0.325	1.000
	(1.24)	(2.49)	(2.16)	(2.83)
InstOwn $_t$	-0.319	-0.324	-0.302	-0.555
	(-6.94)	(-4.95)	(-5.05)	(-4.42)
Analyst $_t$	0.140	0.219	0.164	0.281
	(10.22)	(7.29)	(6.07)	(5.05)
Spread $_t$	11.400	18.147	15.662	25.026
	(16.24)	(7.82)	(7.35)	(5.64)
Fixed Effects	IY	IY	IY	IY
Observations	34,642	34,642	34,642	34,642
R^2_{Adj}	43.18%	25.11%	29.77%	34.38%

Table 5

Endogeneity tests using a natural experiment

This table presents the endogeneity tests using a natural experiment. We regress corporate innovation outcome variables measured in year *t+2* on news coverage measures in year *t*, including other control variables and unreported firm- and year-fixed effects (*FY*). The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the sum of patent values scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. We focus on the sample of 20,157 firm-year observations for news coverage variable from 2000 to 2005 and innovation outcome variables from 2002 to 2007. During this period, the Dow Jones NewsPlus was launch in March 2003. $Post_{NewsPlus}$ is a dummy variable equal to one if year *t* is between 2003 and 2005. $News_{High}$ is dummy equal to one if firms have news coverage above sample median in year *t*. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity.

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6
$News_t \times Post_{NewsPlus}$	**-0.034**	**-0.042**	**-0.070**	0.370	0.074	0.554
	(-1.72)	**(-2.94)**	**(-3.19)**	(2.89)	(0.87)	(2.93)
$News_t \times Post_{NewsPlus} \times News_{High}$				**-0.390**	**-0.113**	**-0.646**
				(-3.23)	**(-1.41)**	**(-3.76)**
$News_t$	0.020	-0.004	0.008	0.011	-0.007	0.026
	(0.78)	(-0.23)	(0.29)	(0.44)	(-0.37)	(0.56)
$Assets_t$	0.077	0.058	0.069	0.080	0.059	0.145
	(2.78)	(3.65)	(4.18)	(2.88)	(3.70)	(3.72)
$R\&D_t$	-0.006	-0.037	-0.040	0.003	-0.034	-0.046
	(-0.03)	(-0.29)	(-0.37)	(0.01)	(-0.27)	(-0.17)
Age_t	-0.190	-0.108	0.048	-0.188	-0.108	-0.187
	(-1.97)	(-1.79)	(0.79)	(-1.95)	(-1.77)	(-1.31)
ROA_t	-0.031	0.008	-0.009	-0.029	0.008	-0.015
	(-0.54)	(0.25)	(-0.33)	(-0.50)	(0.28)	(-0.20)
PPE_t	0.095	-0.008	0.090	0.100	-0.007	0.127
	(0.75)	(-0.10)	(1.13)	(0.78)	(-0.09)	(0.68)
$Leverage_t$	-0.257	-0.158	-0.189	-0.252	-0.157	-0.405
	(-2.98)	(-2.85)	(-3.33)	(-2.92)	(-2.82)	(-3.23)
$Capex_t$	-0.048	0.069	-0.111	-0.056	0.067	-0.098
	(-0.25)	(0.62)	(-1.07)	(-0.29)	(0.60)	(-0.38)
$TobinQ_t$	0.030	0.020	0.020	0.030	0.020	0.050
	(4.00)	(4.50)	(4.76)	(3.94)	(4.47)	(4.89)
$KZIndex_t$	-0.055	-0.032	-0.032	-0.054	-0.031	-0.077
	(-2.29)	(-2.11)	(-2.71)	(-2.28)	(-2.10)	(-2.53)
$HIndex_t$	0.045	0.141	0.122	0.033	0.138	0.289
	(0.11)	(0.61)	(0.51)	(0.08)	(0.60)	(0.49)
$HIndex^2_t$	-0.082	-0.165	-0.152	-0.079	-0.165	-0.410
	(-0.20)	(-0.69)	(-0.59)	(-0.19)	(-0.68)	(-0.64)
$InstOwn_t$	-0.055	-0.015	-0.010	-0.048	-0.013	-0.007
	(-0.91)	(-0.40)	(-0.27)	(-0.79)	(-0.35)	(-0.08)
$Analyst_t$	-0.028	-0.022	-0.008	-0.028	-0.022	-0.029
	(-1.45)	(-1.77)	(-0.69)	(-1.48)	(-1.78)	(-1.08)
$Spread_t$	3.448	1.483	1.158	3.498	1.497	5.198
	(3.22)	(2.42)	(2.07)	(3.27)	(2.44)	(3.71)
$Post_{NewsPlus}$	-0.506	-0.233	-0.320	-0.548	-0.245	-0.819
	(-10.72)	(-7.91)	(-10.07)	(-11.04)	(-7.81)	(-10.90)
$News_{High}$	-0.003	0.012	0.021	0.033	0.022	0.077
	(-0.18)	(0.98)	(1.74)	(1.38)	(1.51)	(2.22)
Fixed Effects	FY	FY	FY	FY	FY	FY
Observations	20,157	20,157	20,157	20,157	20,157	20,157
R^2_{Adj}	58.18%	80.00%	89.98%	58.21%	80.00%	78.68%

Table 6

Additional endogeneity tests

This table presents the additional endogeneity tests based on news sentiment, controlling for past innovation, and using change-in-change specification. We regress corporate innovation outcome variables measured in year *t+2* on news coverage measures in year *t*. The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the sum of patent values scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. The models include other control variables and unreported firm- and year-fixed effects (*FY*), or industry- and year-fixed effects (*IY*). Panel A presents the tests on positive news ($News_{Positive}$) versus negative news ($News_{Negative}$); Panel B presents the tests controlling for innovation outcome variables in prior year; and Panel C presents the tests based on the change-in-change specification. The full panel sample comprises 36,782 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012, and sample size is restricted to 28,780 in change-in-change tests. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity.

Panel A: Endogeneity Tests on News Sentiment

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3
$News_{Positive\ t}$	**-0.081**	**-0.135**	**-0.114**
	(-2.49)	**(-3.31)**	**(-2.04)**
$News_{Negative\ t}$	**-0.187**	**-0.295**	**-0.073**
	(-6.22)	**(-9.01)**	**(-1.75)**
$Assets_t$	0.091	0.117	0.132
	(5.22)	(7.95)	(7.67)
$R\&D_t$	-0.181	-0.280	-0.187
	(-1.37)	(-2.67)	(-1.70)
Age_t	0.037	0.188	-0.255
	(0.61)	(3.27)	(-4.26)
ROA_t	-0.064	-0.064	-0.037
	(-1.80)	(-2.58)	(-1.39)
PPE_t	0.133	0.117	0.098
	(1.68)	(1.68)	(1.23)
$Leverage_t$	-0.182	-0.139	-0.159
	(-3.09)	(-2.61)	(-2.63)
$Capex_t$	0.036	0.113	0.141
	(0.32)	(1.36)	(1.65)
$TobinQ_t$	0.042	0.041	0.026
	(7.99)	(10.16)	(5.80)
$KZIndex_t$	-0.033	-0.021	-0.013
	(-2.52)	(-2.15)	(-1.35)
$HIndex_t$	0.747	1.042	0.828
	(2.44)	(3.64)	(2.80)
$HIndex^2_t$	-0.679	-0.958	-0.908
	(-2.33)	(-3.28)	(-2.97)
$InstOwn_t$	-0.064	-0.032	-0.035
	(-1.57)	(-0.87)	(-0.82)
$Analyst_t$	0.010	0.020	-0.006
	(0.75)	(1.75)	(-0.47)
$Spread_t$	6.303	5.909	0.188
	(8.22)	(9.67)	(0.29)
Fixed Effects	FY	FY	FY
Observations	36,782	36,782	36,782
R^2_{Adj}	45.48%	56.02%	74.79%

Table 6 - Continued

Panel B: Endogeneity Tests Controlling for Past Innovation Outcomes

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6
$News_t$	**-0.048**	**-0.098**	**-0.068**	**-0.063**	**-0.122**	**-0.074**
	(-4.55)	**(-8.60)**	**(-3.05)**	**(-4.74)**	**(-8.05)**	**(-3.24)**
$CitaPat_t$	0.237					
	(23.72)					
$PValue_t$		0.440				
		(41.91)				
$Patent_t$			0.186			
			(9.60)			
$\Delta\ CitaPat_t$				0.014		
				(2.21)		
$\Delta\ PValue_t$					0.176	
					(19.68)	
$\Delta\ Patent_t$						0.144
						(10.75)
$Assets_t$	0.049	0.046	0.107	0.085	0.112	0.131
	(3.45)	(4.31)	(6.74)	(4.92)	(7.92)	(7.97)
$R\&D_t$	-0.230	-0.327	-0.222	-0.181	-0.263	-0.182
	(-1.91)	(-3.73)	(-2.18)	(-1.37)	(-2.59)	(-1.71)
Age_t	0.060	0.131	-0.262	0.038	0.179	-0.225
	(1.24)	(3.27)	(-4.74)	(0.63)	(3.23)	(-3.95)
ROA_t	-0.047	-0.030	-0.031	-0.061	-0.066	-0.047
	(-1.48)	(-1.43)	(-1.21)	(-1.73)	(-2.71)	(-1.79)
PPE_t	0.091	0.026	0.062	0.129	0.115	0.108
	(1.38)	(0.49)	(0.85)	(1.62)	(1.71)	(1.41)
$Leverage_t$	-0.123	-0.061	-0.134	-0.185	-0.136	-0.158
	(-2.46)	(-1.49)	(-2.38)	(-3.13)	(-2.63)	(-2.72)
$Capex_t$	0.008	0.110	0.138	0.039	0.100	0.119
	(0.08)	(1.54)	(1.67)	(0.35)	(1.24)	(1.43)
$TobinQ_t$	0.029	0.027	0.023	0.042	0.040	0.025
	(6.13)	(7.88)	(5.41)	(7.97)	(10.10)	(5.86)
$KZIndex_t$	-0.027	-0.018	-0.013	-0.034	-0.020	-0.012
	(-2.13)	(-2.05)	(-1.41)	(-2.59)	(-2.19)	(-1.33)
$HIndex_t$	0.601	0.725	0.717	0.749	1.014	0.802
	(2.38)	(3.49)	(2.68)	(2.43)	(3.65)	(2.82)
$HIndex^2_t$	-0.573	-0.713	-0.809	-0.679	-0.928	-0.874
	(-2.37)	(-3.40)	(-2.99)	(-2.32)	(-3.28)	(-2.97)
$InstOwn_t$	-0.051	-0.015	-0.022	-0.068	-0.038	-0.030
	(-1.49)	(-0.56)	(-0.55)	(-1.66)	(-1.04)	(-0.74)
$Analyst_t$	0.005	0.007	-0.014	0.011	0.021	-0.006
	(0.41)	(0.74)	(-1.12)	(0.80)	(1.88)	(-0.46)
$Spread_t$	4.195	3.571	-0.528	6.277	5.725	0.013
	(6.32)	(7.47)	(-0.88)	(8.16)	(9.61)	(0.02)
Fixed Effects	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	36,782	36,782	36,782
R^2_{Adj}	50.05%	65.03%	75.45%	45.40%	57.26%	75.32%

Table 6 - Continued

Panel C: Endogeneity Tests Using Change-in-Change Specification

	$\Delta CitaPat_{t+2}$	$\Delta PValue_{t+2}$	$\Delta Patent_{t+2}$
Variable	M1	M2	M3
Δ *News* $_t$	**-0.056**	**-0.076**	**-0.209**
	(-4.50)	**(-7.47)**	**(-6.39)**
Δ *Assets* $_t$	-0.040	-0.025	-0.058
	(-1.83)	(-1.69)	(-1.97)
Δ *R&D* $_t$	-0.218	-0.077	-0.214
	(-1.67)	(-0.79)	(-2.02)
Δ Age_t	0.046	0.173	1.172
	(0.37)	(1.97)	(5.35)
Δ ROA_t	-0.023	0.000	0.006
	(-0.69)	(0.00)	(0.16)
Δ *PPE* $_t$	-0.141	-0.061	-0.060
	(-1.81)	(-1.07)	(-0.71)
Δ *Leverage* $_t$	-0.081	0.039	0.053
	(-1.44)	(0.86)	(0.77)
Δ *Capex* $_t$	0.113	-0.044	-0.063
	(1.00)	(-0.59)	(-0.64)
Δ *TobinQ* $_t$	0.018	0.009	0.011
	(2.90)	(2.18)	(2.03)
Δ *KZIndex* $_t$	-0.034	-0.017	-0.026
	(-2.24)	(-1.63)	(-2.22)
Δ *HIndex* $_t$	0.482	0.101	0.700
	(1.56)	(0.47)	(1.76)
Δ $HIndex^2{}_t$	-0.329	-0.102	-0.589
	(-1.09)	(-0.50)	(-1.58)
Δ *InstOwn* $_t$	-0.071	-0.012	0.090
	(-1.94)	(-0.39)	(1.83)
Δ *Analyst* $_t$	-0.019	0.008	0.003
	(-1.46)	(0.81)	(0.17)
Δ *Spread* $_t$	0.955	0.008	-3.659
	(1.41)	(0.02)	(-4.78)
Fixed Effects	IY	IY	IY
Observations	28,780	28,780	28,780
R^2_{Adj}	4.58%	3.74%	5.61%

Table 7

Tests on economic channels based on news content

This table presents the tests based on news content on the economic channels through which news coverage affects corporate innovation outcomes. The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the sum of patent values scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. The main variables of interest are the news coverage variables, which are the numbers of news articles related to earnings ($News_{Earnings}$), product ($News_{Product}$), financing ($News_{Financing}$), and governance ($News_{Governance}$) news estimated in year *t*. The models also include the news coverage for other news content ($News_{Other}$), as well as other control variables and unreported firm- and year-fixed effects (*FY*). The coefficients on control variables are omitted for brevity. The full panel sample comprises 36,782 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity.

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15
$News_{Earnings\ t}$	**-0.378**	**-0.183**	**-0.521**										**-0.344**	**-0.132**	**-0.482**
	(-5.36)	**(-2.50)**	**(-5.18)**										**(-4.76)**	**(-1.79)**	**(-4.77)**
$News_{Product\ t}$				**-0.281**	**-0.038**	**-0.071**							**-0.262**	**-0.039**	**-0.046**
				(-2.27)	**(-0.17)**	**(-0.18)**							**(-2.09)**	**(-0.17)**	**(-0.12)**
$News_{Financing\ t}$							**0.372**	**0.373**	**1.013**				**0.352**	**0.350**	**0.981**
							(1.77)	**(1.25)**	**(2.65)**				**(1.71)**	**(1.17)**	**(2.55)**
$News_{Governance\ t}$										**-0.055**	**-0.083**	**-0.073**	**-0.044**	**-0.078**	**-0.056**
										(-2.43)	**(-4.41)**	**(-2.08)**	**(-1.96)**	**(-4.19)**	**(-1.59)**
$News_{Other\ t}$	-0.041	-0.171	-0.046	-0.063	-0.185	-0.086	-0.078	-0.193	-0.107	-0.065	-0.177	-0.080	-0.038	-0.172	-0.060
	(-1.94)	(-6.21)	(-1.15)	(-3.20)	(-7.13)	(-2.27)	(-3.67)	(-7.00)	(-2.77)	(-3.19)	(-6.71)	(-2.09)	(-1.72)	(-6.06)	(-1.51)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782	36,782
R^2_{Adj}	45.39%	55.88%	74.85%	45.33%	55.86%	74.79%	45.33%	55.87%	74.81%	45.35%	55.95%	74.81%	45.42%	55.96%	74.88%

Table 8

Tests on economic channels based on interaction variables

This table presents the tests based on interaction variables on the economic channels through which news coverage affects corporate innovation outcomes. The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the sum of patent values scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. The main variables of interest are the news coverage variables, the numbers of news articles related to earnings ($News_{Earnings}$), product ($News_{Product}$), financing ($News_{Financing}$), and governance ($News_{Governance}$) news estimated in year *t*, which are interacted with the factors associated with the relevant economic channels. The models also include the news coverage of other news content ($News_{Other}$), other control variables and unreported firm- and year-fixed effects (*FY*). The coefficients on other control variables are omitted for brevity. The full panel sample comprises 36,782 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012, which varies according to the availability of the factors associated with the economic channels. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity.

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
$News_{Earnings\ t} \times Short\ Horizon_t$	**-0.351**	**-0.549**	**-0.657**									
	(-2.17)	**(-3.40)**	**(-3.21)**									
$Short\ Horizon_t$	**0.062**	**0.053**	**-0.009**									
	(2.57)	**(2.84)**	**(-0.44)**									
$News_{Product\ t} \times Fluidity_t$				**0.020**	**0.038**	**0.010**						
				(0.56)	**(0.90)**	**(0.17)**						
$Fluidity_t$				**0.008**	**0.004**	**0.001**						
				(2.58)	**(1.55)**	**(0.25)**						
$News_{Financing\ t} \times WWIndex_t$							**3.162**	**2.771**	**-0.630**			
							(2.48)	**(1.93)**	**(-0.37)**			
$WWIndex_t$							**-0.175**	**-0.115**	**-0.071**			
							(-3.29)	**(-2.62)**	**(-1.60)**			
$News_{Governance\ t} \times BIndependence_t$										**-0.341**	**-0.495**	**-0.050**
										(-2.41)	**(-3.34)**	**(-0.19)**
$BIndependence_t$										**0.299**	**0.358**	**0.142**
										(2.43)	**(3.04)**	**(1.02)**
$News_{Earnings\ t}$	-0.195	0.107	-0.183	-0.344	-0.143	-0.450	-0.349	-0.137	-0.478	-0.253	-0.062	-0.402
	(-2.03)	(1.01)	(-1.32)	(-4.59)	(-1.88)	(-4.35)	(-4.83)	(-1.85)	(-4.71)	(-3.30)	(-0.66)	(-3.07)
$News_{Product\ t}$	-0.259	-0.035	-0.043	-0.417	-0.326	-0.071	-0.270	-0.044	-0.057	-0.288	-0.275	-0.206
	(-2.07)	(-0.16)	(-0.11)	(-1.39)	(-0.88)	(-0.13)	(-2.14)	(-0.19)	(-0.15)	(-2.36)	(-1.15)	(-0.51)
$News_{Governance\ t}$	-0.045	-0.079	-0.055	-0.043	-0.076	-0.062	-0.045	-0.079	-0.057	0.253	0.331	-0.058
	(-1.99)	(-4.16)	(-1.57)	(-1.87)	(-4.11)	(-1.74)	(-2.01)	(-4.20)	(-1.60)	(2.28)	(2.92)	(-0.27)
$News_{Financing\ t}$	0.346	0.346	0.984	0.348	0.262	0.892	0.093	0.132	1.033	0.091	0.161	1.068
	(1.69)	(1.19)	(2.52)	(1.66)	(0.85)	(2.32)	(0.36)	(0.34)	(2.20)	(0.36)	(0.44)	(2.18)
$News_{Other\ t}$	-0.038	-0.171	-0.059	-0.040	-0.176	-0.055	-0.034	-0.169	-0.064	-0.007	-0.130	-0.024
	(-1.69)	(-6.03)	(-1.48)	(-1.72)	(-6.10)	(-1.31)	(-1.54)	(-5.88)	(-1.59)	(-0.32)	(-4.20)	(-0.55)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	34,400	34,400	34,400	36,653	36,653	36,653	21,192	21,192	21,192
R^2_{Adj}	45.44%	55.99%	74.91%	45.98%	56.27%	75.16%	45.63%	56.15%	74.91%	48.81%	56.57%	74.83%

Table 9

News coverage and innovator quality

This table presents the tests on whether the impact of media on innovation outcomes is associated with the quality of innovators. We regress corporate innovation outcome variables measured in year *t+2* on news coverage measures in year *t*. The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the summed values of patents scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. The proxies of innovator quality are the annual truncation adjusted citation-to-patent ratio averaged from year *t-3* to *t-1* ($IQuality_{Citation}$), and the sum of patent values scaled by market value of equity averaged from year *t-3* to *t-1* ($IQuality_{PValue}$). The models include other control variables and unreported firm- and year-fixed effects (*FY*). The full panel sample comprises 36,782 firm-year observations for news coverage variable from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity.

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6
$News_t \times IQuality_{Citation\ t}$	**-0.187**	**-0.153**	**-0.112**			
	(-4.91)	**(-4.69)**	**(-2.88)**			
$IQuality_{Citation\ t}$	0.070	0.175	0.065			
	(2.06)	(6.55)	(2.34)			
$News_t \times IQuality_{PValue\ t}$				**-1.145**	**-0.312**	**-0.214**
				(-3.99)	**(-3.52)**	**(-2.07)**
$IQuality_{PValue\ t}$				3.125	4.825	6.123
				(6.34)	(15.37)	(20.70)
$News_t$	0.019	-0.061	-0.030	-0.007	-0.027	-0.091
	(1.32)	(-4.01)	(-1.36)	(-0.26)	(-2.07)	(-7.19)
$Assets_t$	0.078	0.104	0.129	0.107	0.044	0.061
	(4.54)	(7.14)	(7.46)	(6.40)	(2.65)	(4.66)
$R\&D_t$	-0.187	-0.298	-0.193	-0.228	-0.241	-0.351
	(-1.42)	(-2.85)	(-1.76)	(-2.14)	(-1.83)	(-3.51)
Age_t	0.044	0.187	-0.264	-0.250	-0.005	0.115
	(0.73)	(3.31)	(-4.38)	(-4.25)	(-0.09)	(2.44)
ROA_t	-0.061	-0.058	-0.040	-0.024	-0.023	-0.012
	(-1.73)	(-2.37)	(-1.52)	(-0.93)	(-0.68)	(-0.50)
PPE_t	0.120	0.099	0.090	0.069	0.077	0.041
	(1.53)	(1.43)	(1.14)	(0.89)	(1.01)	(0.65)
$Leverage_t$	-0.182	-0.138	-0.160	-0.153	-0.159	-0.111
	(-3.13)	(-2.62)	(-2.66)	(-2.57)	(-2.78)	(-2.32)
$Capex_t$	0.032	0.121	0.143	0.155	0.052	0.139
	(0.30)	(1.48)	(1.68)	(1.85)	(0.48)	(1.72)
$TobinQ_t$	0.041	0.039	0.026	0.024	0.036	0.033
	(7.69)	(9.66)	(5.69)	(5.33)	(6.76)	(8.50)
$KZIndex_t$	-0.033	-0.021	-0.012	-0.016	-0.038	-0.027
	(-2.52)	(-2.21)	(-1.26)	(-1.76)	(-2.93)	(-2.84)
$HIndex_t$	0.677	0.954	0.776	0.703	0.544	0.771
	(2.22)	(3.37)	(2.63)	(2.47)	(1.87)	(3.13)
$HIndex^2_t$	-0.600	-0.869	-0.856	-0.793	-0.507	-0.733
	(-2.07)	(-3.01)	(-2.81)	(-2.73)	(-1.86)	(-2.93)
$InstOwn_t$	-0.070	-0.038	-0.034	-0.029	-0.047	-0.009
	(-1.73)	(-1.03)	(-0.80)	(-0.70)	(-1.24)	(-0.29)
$Analyst_t$	0.012	0.022	-0.004	-0.010	0.000	0.008
	(0.94)	(1.95)	(-0.32)	(-0.75)	(0.01)	(0.80)
$Spread_t$	6.186	5.647	0.134	-0.506	4.745	3.928
	(8.11)	(9.32)	(0.21)	(-0.84)	(6.39)	(7.14)
Fixed Effects	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	36,782	36,782	36,782
R^2_{Adj}	45.87%	56.42%	74.90%	75.26%	47.40%	60.63%

Table 10

News coverage and alternative growth measures

This table presents the tests on the association between news coverage and alternative growth measures. The dependent variables are four proxies of firm growth, the principal component of following three growth metrics (*Growth* $_{Overall}$), the industry adjusted growth of cash flow from operation measured in year *t+3* (*Growth* $_{CFO}$), the discretionary selling, general and administrative expenses measured in year *t* (*Growth* $_{SG\&A}$)., and the discretionary research and development expenses measured in year *t* (*Growth* $_{R\&D}$). News coverage (*News*) is the number of news articles estimated in year *t*. The models include other control variables and unreported firm- and year-fixed effects (*FY)*. Panel A presents the results of OLS regression. Panel B presents the results from the second stage of the two-stage instrumental variable analysis while the first stage results are the same as reported in Table 4. The full panel sample comprises 36,782 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012, which varies according to the availability of the growth metrics and is further restricted in the instrumental variable analysis. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity.

Panel A: OLS Regression

	Growth $_{Overall}$	*Growth* $_{CFO\ t+3}$	*Growth* $_{SG\&A\ t}$	*Growth* $_{R\&D\ t}$
Variable	M1	M2	M3	M4
News $_t$	**-0.041**	**-0.003**	**-0.005**	**-0.005**
	(-2.40)	**(-2.46)**	**(-2.16)**	**(-3.58)**
Assets $_t$	0.243	-0.001	0.014	0.038
	(6.30)	(-0.49)	(3.18)	(12.01)
R&D $_t$	5.700	-0.058	0.379	0.615
	(14.05)	(-1.72)	(7.47)	(21.84)
Age $_t$	-0.717	-0.019	-0.085	-0.056
	(-5.42)	(-2.50)	(-6.25)	(-5.20)
ROA $_t$	0.637	-0.018	0.043	0.059
	(7.29)	(-2.11)	(3.78)	(9.10)
PPE $_t$	0.202	-0.011	0.012	-0.025
	(1.07)	(-0.75)	(0.50)	(-1.40)
Leverage $_t$	0.021	-0.012	0.025	-0.014
	(0.20)	(-1.36)	(2.05)	(-1.48)
Capex $_t$	0.255	-0.004	0.098	0.018
	(0.89)	(-0.15)	(3.16)	(0.71)
TobinQ $_t$	0.119	-0.001	0.021	0.010
	(9.13)	(-0.76)	(12.21)	(10.33)
KZIndex $_t$	-0.330	-0.001	-0.032	-0.029
	(-6.10)	(-0.15)	(-5.15)	(-7.73)
HIndex $_t$	0.040	-0.002	-0.116	0.056
	(0.10)	(-0.05)	(-2.00)	(1.60)
HIndex ^2_t	0.261	0.011	0.129	-0.026
	(0.69)	(0.34)	(2.53)	(-0.82)
InstOwn $_t$	-0.322	-0.010	-0.038	-0.026
	(-4.62)	(-1.81)	(-4.49)	(-4.36)
Analyst $_t$	-0.089	-0.001	-0.011	-0.013
	(-3.72)	(-0.32)	(-3.72)	(-5.79)
Spread $_t$	-0.180	-0.117	-0.199	0.174
	(-0.12)	(-0.82)	(-1.11)	(1.39)
Fixed Effects	FY	FY	FY	FY
Observations	17,000	29,846	30,317	21,826
R^2_{Adj}	68.30%	13.60%	70.25%	62.01%

Panel B: Instrument Variable Analysis

Variable	*Growth* $_{Overall}$ M1	*Growth* $_{CFO\ t+3}$ M2	*Growth* $_{SG\&A\ t}$ M3	*Growth* $_{R\&D\ t}$ M4
News $_{Predict\ t}$	**-1.570**	**-0.034**	**-0.125**	**-0.135**
	(-2.87)	**(-2.04)**	**(-1.42)**	**(-3.65)**
Assets $_t$	0.550	0.010	0.034	0.054
	(3.27)	(1.99)	(1.24)	(4.73)
R&D $_t$	7.742	-0.012	0.736	0.798
	(30.15)	(-0.84)	(17.67)	(44.24)
Age $_t$	0.080	0.003	0.001	0.008
	(0.73)	(0.87)	(0.07)	(1.08)
ROA $_t$	0.522	-0.036	-0.008	0.089
	(5.57)	(-5.71)	(-0.59)	(13.81)
PPE $_t$	-1.118	-0.007	-0.172	-0.059
	(-7.01)	(-1.19)	(-7.18)	(-5.07)
Leverage $_t$	-0.463	-0.027	-0.047	-0.046
	(-2.22)	(-4.05)	(-1.47)	(-3.32)
Capex $_t$	2.633	0.044	0.381	0.165
	(5.85)	(2.51)	(6.26)	(5.27)
TobinQ $_t$	0.227	0.004	0.034	0.014
	(5.42)	(3.25)	(5.12)	(5.17)
KZIndex $_t$	-0.229	-0.005	-0.025	-0.019
	(-4.96)	(-1.69)	(-3.69)	(-6.27)
HIndex $_t$	-0.639	-0.031	-0.144	-0.026
	(-2.04)	(-2.90)	(-2.98)	(-1.17)
HIndex $^2{}_t$	0.940	0.038	0.157	0.051
	(2.63)	(3.10)	(2.66)	(2.08)
InstOwn $_t$	-0.471	-0.012	-0.041	-0.044
	(-2.56)	(-2.06)	(-1.37)	(-3.55)
Analyst $_t$	0.189	0.008	0.027	0.011
	(2.42)	(2.94)	(2.14)	(2.04)
Spread $_t$	18.983	0.431	1.123	1.697
	(2.91)	(2.05)	(1.09)	(3.87)
Fixed Effects	FY	FY	FY	FY
Observations	17,000	29,846	30,317	21,826
R^2_{Adj}	34.55%	0.77%	19.53%	41.12%

Internet Appendix

"Does the media spotlight burn or spur innovation?"

This online appendix provides additional tables for "Does the media spotlight burn or spur innovation?" We summarize the content as follows:

Internet Appendix 1

Variable definitions and data sources in Internet appendix

This appendix presents variable definitions and data sources for metrics used only in the internet appendix.

Variable	Definition
Innovation outcome variables	
Citation	Number of citations of patents for patents granted in one year based on the data provided by *KPSS* (Kogan, Papanikolaou, Seru, and Stoffman, 2017) and the data collected from *Google USPTO Bulk Downloads*. The number of citations per patent is adjusted for truncation, where the raw value is divided by the sample annual mean (Hall, Jaffe, and Trajtenberg, 2001). Log value of *Citation* is taken in the regression analysis.
$PValue_{Raw}$	Sum of patent values for patents granted in one year based on the data provided by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads*. The patent value is estimated based on the stock return following patent grant date using the approach from *KPSS* (2017). Log value of $PValue_{Raw}$ is taken in the regression analysis.
$PValue_{Ave}$	Average patent value for patents granted in one year based on the data provided by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads*. The patent value is estimated based on the stock return following patent grant date using the approach from *KPSS* (2017). Log value of $PValue_{Ave}$ is taken in the regression analysis.
$Innovation_{MAdj}$	Scaled measures of the average number of citations per patent ($CitaPat_{MAdj}$), sum of patent values ($PValue_{MAdj}$ - same as *PValue* in main tables), number of patents ($Patent_{AAdj}$) by market value of equity for patents granted in one year based on the data provided by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads* as well as *Compustat Annual*. $PValue_{MAdj}$ is essentially the same as *PValue* in the main analysis, which is noted differently in Internet Appendix merely for sake of presentation consistency. Log value of $Innovation_{MAdj}$ is taken in the regression analysis.
$Innovation_{AAdj}$	Scaled measures of the average number of citations per patent ($CitaPat_{AAdj}$), sum of patent values ($PValue_{AAdj}$), number of patents ($Patent_{AAdj}$) by total assets for patents granted in one year based on the data provided by *KPSS* (2016) and the data collected from *Google USPTO Bulk Downloads* as well as *Compustat Annual*. Log value of $Innovation_{AAdj}$ is taken in the regression analysis.
$Innovation_{EAdj}$	Scaled measures of the average number of citations per patent ($CitaPat_{EAdj}$), sum of patent values ($PValue_{EAdj}$), number of patents ($Patent_{EAdj}$) by number of employees, for patents granted in one year based on the data provided by *KPSS* (2017) and the data collected from *Google USPTO Bulk Downloads* as well as *Compustat Annual*. Log value of $Innovation_{EAdj}$ is taken in the regression analysis.
News coverage variables	
$News_{Madj}$	Scaled measures of the number of news articles by market value of equity in one year based on *RavenPack.*
$News_{AAdj}$	Scaled measures of the number of news articles by total assets in one year based on *RavenPack.*
$News_{EAdj}$	Scaled measures of the number of news articles by number of employees in one year based on *RavenPack.*

Internet Appendix 1 - Continued

Variable	Definition
News coverage variables	
$News_{Repeated}$	Number of repeated news articles in one year based on *RavenPack* and divided by 100 in regression analysis.
$News_{Original}$	Number of original news articles in one year based on *RavenPack*.
$News_{Press\ Release}$	Number of press releases issued by a firm in one year based on *RavenPack*.
$News_{TRNA}$	Number of news articles in one year based on *Thomson Reuters News Analytics* (*TRNA*).
$News_{TRNA+RavenPack,\ 1}$	Number of news articles in one year based on *RavenPack,* which is complemented by the *TRNA* data if the *RavenPack* information is missing.
$News_{TRNA+RavenPack,\ 2}$	Sum of numbers of news articles in one year from both *RavenPack* and *TRNA* databases.

Internet Appendix 2

Alternative measures of innovation outcome

This table presents regressions of corporate innovation outcome variables on news coverage, using alternative measures of innovation outcome, and including other control variables and unreported firm- and year-fixed effects (*FY*). From M1 to M3, the corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the sum of patent values scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+3*. From M4 to M6, the corporate innovation outcome variables are the logarithm values of the number of citations (*Citation*), the sum of patent values ($PValue_{Raw}$), and the average patent value ($PValue_{Ave}$) for patents granted in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. The full panel sample comprises 36,782 firm-year observations for news coverage variable from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

	$CitaPat_{t+3}$	$PValue_{t+3}$	$Patent_{t+3}$	$Citation_{t+2}$	$PValue_{Raw\ t+2}$	$PValue_{Ave\ t+2}$
Variable	M1	M2	M3	M4	M5	M6
$News_t$	**-0.067**	**-0.007**	**-0.038**	**-0.162**	**-0.373**	**-0.186**
	(-5.53)	**(-8.42)**	**(-1.75)**	**(-5.51)**	**(-8.67)**	**(-8.43)**
$Assets_t$	0.068	0.004	0.111	0.188	0.092	0.010
	(4.38)	(6.18)	(6.09)	(6.58)	(2.90)	(0.62)
$R\&D_t$	-0.127	-0.010	-0.198	-0.371	-0.332	-0.132
	(-1.12)	(-2.15)	(-1.71)	(-1.80)	(-2.00)	(-1.49)
Age_t	0.049	0.010	-0.205	0.164	1.004	0.479
	(0.88)	(3.50)	(-3.23)	(1.59)	(7.09)	(6.94)
ROA_t	-0.034	-0.002	-0.008	-0.093	-0.173	-0.097
	(-1.25)	(-2.10)	(-0.29)	(-1.87)	(-4.10)	(-4.07)
PPE_t	0.109	0.001	0.117	0.276	0.163	0.047
	(1.53)	(0.38)	(1.37)	(2.03)	(1.13)	(0.60)
$Leverage_t$	-0.157	-0.006	-0.230	-0.375	-0.252	-0.091
	(-2.99)	(-2.56)	(-3.46)	(-3.78)	(-2.27)	(-1.60)
$Capex_t$	0.133	0.015	0.104	0.057	0.101	0.002
	(1.33)	(3.85)	(1.09)	(0.35)	(0.64)	(0.02)
$TobinQ_t$	0.036	0.002	0.028	0.072	0.069	0.030
	(7.91)	(8.17)	(6.15)	(9.23)	(8.61)	(6.87)
$KZIndex_t$	-0.024	-0.001	-0.004	-0.049	-0.052	-0.031
	(-2.39)	(-1.24)	(-0.45)	(-2.63)	(-3.45)	(-3.78)
$HIndex_t$	0.703	0.051	0.839	1.704	1.894	0.548
	(2.56)	(3.95)	(2.72)	(3.25)	(3.03)	(1.74)
$HIndex^2_t$	-0.690	-0.051	-1.014	-1.678	-1.486	-0.290
	(-2.58)	(-3.95)	(-3.24)	(-3.17)	(-2.35)	(-0.93)
$InstOwn_t$	-0.038	-0.001	-0.048	-0.085	-0.155	-0.077
	(-1.03)	(-0.81)	(-0.97)	(-1.19)	(-1.98)	(-1.90)
$Analyst_t$	-0.006	0.001	-0.024	0.038	0.072	0.015
	(-0.48)	(1.86)	(-1.67)	(1.71)	(3.12)	(1.21)
$Spread_t$	5.295	0.239	1.463	9.591	12.151	5.510
	(7.99)	(8.40)	(2.24)	(8.15)	(9.96)	(8.92)
Fixed Effects	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	36,782	36,782	36,782
R^2_{Adj}	42.25%	48.07%	72.25%	66.64%	61.97%	54.06%

Internet Appendix 3

Scaled measures of news coverage and innovation outcome

This table presents regressions of corporate innovation outcome variables on news coverage, using alternative scaled measures of news coverage and innovation outcome, and including other control variables and unreported firm- and year-fixed effects (*FY*). The corporate innovation outcome variables are logarithm values of the average number of citations per patent, the sum of patent values scaled by market value of equity, and the number of patents scaled by market value of equity ($CitaPat_{MAdj}$, $PValue_{MAdj}$, and $Patent_{MAdj}$), book value of total assets ($CitaPat_{AAdj}$, $PValue_{AAdj}$, and $Patent_{AAdj}$), and number of employees ($CitaPat_{EAdj}$, $PValue_{EAdj}$, and $Patent_{EAdj}$) measured in year *t+2*. The main variables of interest are the number of news articles scaled by market value of equity ($News_{Madj}$), book value of total assets ($News_{AAdj}$), and number of employees ($News_{EAdj}$) estimated in year *t*. The full panel sample comprises 36,782 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

	$CitaPat_{MAdj\ t+2}$	$PValue_{MAdj\ t+2}$	$Patent_{MAdj\ t+2}$	$CitaPat_{AAdj\ +2}$	$PValue_{AAdj\ t+2}$	$Patent_{AAdj\ t+2}$	$CitaPat_{EAdj\ t+2}$	$PValue_{EAdj\ t+2}$	$Patent_{EAdj\ t+2}$
Variable	M1	M2	M3	M4	M5	M6	M7	M8	M9
$News_{Madj\ t}$	**-0.048**	**-0.024**	**-0.048**						
	(-4.76)	**(-3.28)**	**(-4.76)**						
$News_{AAdj\ t}$				**-0.116**	**-0.088**	**-0.116**			
				(-4.79)	**(-4.31)**	**(-4.79)**			
$News_{EAdj\ t}$							**-0.084**	**-0.083**	**-0.084**
							(-4.91)	**(-4.52)**	**(-4.91)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed	FY	FY	FY	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	36,782	36,782	36,782	35,871	35,871	35,871
R^2_{Adj}	29.96%	30.93%	29.96%	37.69%	37.10%	37.69%	43.06%	40.02%	43.06%

Internet Appendix 4

Alternative sample selection excluding firms with limited news coverage or truncated patent information

This table presents regressions of corporate innovation outcome variables on news coverage, using alternative sample selections by excluding firms with limited news coverage, patenting activities, or patent information, and including other control variables and unreported firm- and year-fixed effects (*FY*). The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the summed value of patents scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. The full panel sample comprises 36,782 firm-year observations for news coverage variable from 2000 to 2010 and innovation outcome variables from 2002 to 2012. We restrict the sample by requiring news coverage in year *t* to be positive (*News* > 0), or focusing on the sub-sample period (Year ~ [2000, 2007]). Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

	$News_t > 0$			Year ~ [2000, 2007]		
	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6
$News_t$	**-0.065**	**-0.145**	**-0.075**	**-0.034**	**-0.108**	**-0.145**
	(-4.74)	**(-9.22)**	**(-3.34)**	**(-2.16)**	**(-6.84)**	**(-6.75)**
$Assets_t$	0.091	0.119	0.153	0.081	0.101	0.105
	(4.75)	(7.45)	(8.34)	(3.75)	(6.84)	(6.36)
$R\&D_t$	-0.161	-0.261	-0.156	-0.062	-0.150	-0.154
	(-1.15)	(-2.33)	(-1.35)	(-0.37)	(-1.26)	(-1.42)
Age_t	0.002	0.147	-0.280	-0.041	0.091	0.290
	(0.03)	(2.39)	(-4.27)	(-0.52)	(1.54)	(4.14)
ROA_t	-0.070	-0.058	-0.037	-0.056	-0.038	-0.069
	(-1.85)	(-2.18)	(-1.30)	(-1.18)	(-1.34)	(-2.46)
PPE_t	0.112	0.087	0.105	0.065	0.015	0.073
	(1.23)	(1.09)	(1.19)	(0.64)	(0.20)	(0.91)
$Leverage_t$	-0.183	-0.147	-0.164	-0.210	-0.174	-0.195
	(-2.89)	(-2.56)	(-2.53)	(-3.00)	(-3.33)	(-3.42)
$Capex_t$	0.079	0.139	0.122	0.115	0.243	0.126
	(0.61)	(1.46)	(1.25)	(0.74)	(2.39)	(1.26)
$TobinQ_t$	0.046	0.044	0.028	0.037	0.032	0.035
	(8.01)	(10.06)	(5.95)	(5.88)	(7.70)	(7.97)
$KZIndex_t$	-0.036	-0.023	-0.013	-0.041	-0.024	-0.026
	(-2.55)	(-2.23)	(-1.28)	(-2.22)	(-1.91)	(-2.45)
$HIndex_t$	0.803	1.061	0.809	0.486	0.679	0.791
	(2.44)	(3.48)	(2.55)	(1.44)	(2.67)	(2.73)
$HIndex^2_t$	-0.722	-0.984	-0.910	-0.435	-0.658	-0.748
	(-2.30)	(-3.15)	(-2.74)	(-1.33)	(-2.46)	(-2.41)
$InstOwn_t$	-0.072	-0.044	-0.061	-0.068	-0.013	-0.018
	(-1.66)	(-1.12)	(-1.35)	(-1.37)	(-0.34)	(-0.44)
$Analyst_t$	0.010	0.021	-0.004	-0.015	-0.007	0.017
	(0.72)	(1.68)	(-0.28)	(-0.99)	(-0.57)	(1.39)
$Spread_t$	6.279	6.207	0.123	4.687	3.580	3.353
	(7.69)	(9.41)	(0.18)	(4.73)	(5.54)	(5.04)
Fixed Effects	FY	FY	FY	FY	FY	FY
Observations	33,866	33,866	33,866	27,165	27,165	27,165
R^2_{Adj}	45.12%	55.76%	74.75%	51.08%	68.72%	81.96%

Internet Appendix 5

Alternative clustering techniques

This table presents regressions of corporate innovation outcome variables on news coverage, using alternative clustering techniques, and including other control variables and unreported firm- and year-fixed effects (*FY*). The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the summed value of patents scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year $t+2$. News coverage (*News*) is the number of news articles estimated in year *t*. The full panel sample comprises 36,782 firm-year observations for news coverage variable from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

	Industry Clustering			*State Clustering*		
	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6
$News_t$	**-0.062**	**-0.127**	**-0.078**	**-0.062**	**-0.127**	**-0.078**
	(-3.88)	**(-5.50)**	**(-3.87)**	**(-4.28)**	**(-7.92)**	**(-2.69)**
$Assets_t$	0.085	0.113	0.134	0.085	0.113	0.134
	(1.99)	(2.82)	(4.59)	(4.04)	(7.61)	(4.26)
$R\&D_t$	-0.181	-0.276	-0.186	-0.181	-0.276	-0.186
	(-1.11)	(-1.99)	(-1.63)	(-1.09)	(-2.47)	(-2.05)
Age_t	0.036	0.175	-0.270	0.036	0.175	-0.270
	(0.56)	(2.23)	(-2.73)	(0.38)	(1.86)	(-3.26)
ROA_t	-0.060	-0.059	-0.040	-0.060	-0.059	-0.040
	(-1.61)	(-1.39)	(-1.00)	(-1.50)	(-2.32)	(-1.71)
PPE_t	0.128	0.108	0.096	0.128	0.108	0.096
	(1.76)	(1.80)	(1.14)	(1.46)	(1.78)	(1.35)
$Leverage_t$	-0.185	-0.146	-0.163	-0.185	-0.146	-0.163
	(-3.74)	(-2.85)	(-2.56)	(-2.18)	(-2.37)	(-2.15)
$Capex_t$	0.038	0.121	0.146	0.038	0.121	0.146
	(0.28)	(1.01)	(1.56)	(0.42)	(1.13)	(1.69)
$TobinQ_t$	0.042	0.042	0.027	0.042	0.042	0.027
	(4.09)	(5.55)	(6.80)	(7.25)	(8.30)	(7.61)
$KZIndex_t$	-0.034	-0.022	-0.012	-0.034	-0.022	-0.012
	(-1.79)	(-1.67)	(-0.88)	(-2.61)	(-2.03)	(-1.22)
$HIndex_t$	0.740	1.022	0.817	0.740	1.022	0.817
	(0.90)	(1.58)	(1.47)	(3.35)	(3.30)	(3.33)
$HIndex^2_t$	-0.670	-0.940	-0.900	-0.670	-0.940	-0.900
	(-0.91)	(-1.72)	(-1.85)	(-2.94)	(-2.83)	(-3.45)
$InstOwn_t$	-0.068	-0.037	-0.033	-0.068	-0.037	-0.033
	(-1.53)	(-0.93)	(-1.10)	(-0.85)	(-0.59)	(-0.81)
$Analyst_t$	0.010	0.022	-0.005	0.010	0.022	-0.005
	(0.70)	(1.07)	(-0.33)	(0.63)	(1.41)	(-0.45)
$Spread_t$	6.266	5.909	0.220	6.266	5.909	0.220
	(5.10)	(3.90)	(0.24)	(2.50)	(2.92)	(0.26)
Fixed Effects	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	36,782	36,782	36,782
R^2_{Adj}	45.37%	55.91%	74.83%	45.37%	55.91%	74.83%

Internet Appendix 6

Additional tests on news originality and press release

This table presents regressions of corporate innovation outcome variables on additional news coverage measures based on news originality and press release, including other control variables and unreported firm- and year-fixed effects (*FY*). The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the summed value of patents scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage (*News*) is the number of news articles estimated in year *t*. The additional news coverage measures are the number of repeated ($News_{Repeated}$), original news articles ($News_{Original}$), and the number of press releases by firm ($News_{Press\ Release}$) estimated in year *t*. The full panel sample comprises 36,782 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6
$News_{Repeated\ t}$	**-0.050**	**-0.170**	**-0.210**			
	(-1.50)	**(-4.65)**	**(-4.03)**			
$News_{Original\ t}$	**-0.115**	**-0.123**	**0.018**			
	(-4.53)	**(-4.25)**	**(0.50)**			
$News_{Press\ Release}$				**-0.070**	**0.081**	**-0.269**
				(-0.85)	**(1.01)**	**(-2.74)**
$News_t$				**-0.081**	**-0.139**	**-0.053**
				(-5.65)	**(-7.91)**	**(-2.34)**
$Assets_t$	0.090	0.115	0.130	0.089	0.113	0.135
	(5.22)	(7.79)	(7.57)	(5.14)	(7.63)	(7.83)
$R\&D_t$	-0.178	-0.277	-0.190	-0.178	-0.278	-0.184
	(-1.35)	(-2.63)	(-1.74)	(-1.35)	(-2.64)	(-1.68)
Age_t	0.035	0.182	-0.268	0.035	0.185	-0.257
	(0.58)	(3.16)	(-4.45)	(0.58)	(3.20)	(-4.29)
ROA_t	-0.059	-0.059	-0.041	-0.061	-0.058	-0.041
	(-1.68)	(-2.39)	(-1.56)	(-1.72)	(-2.35)	(-1.54)
PPE_t	0.129	0.110	0.097	0.128	0.112	0.096
	(1.62)	(1.56)	(1.21)	(1.61)	(1.59)	(1.20)
$Leverage_t$	-0.189	-0.148	-0.160	-0.186	-0.149	-0.156
	(-3.20)	(-2.76)	(-2.64)	(-3.16)	(-2.79)	(-2.59)
$Capex_t$	0.044	0.122	0.138	0.041	0.124	0.141
	(0.40)	(1.46)	(1.61)	(0.38)	(1.48)	(1.65)
$TobinQ_t$	0.043	0.042	0.027	0.043	0.042	0.026
	(8.10)	(10.30)	(5.84)	(8.03)	(10.29)	(5.71)
$KZIndex_t$	-0.033	-0.021	-0.013	-0.033	-0.021	-0.012
	(-2.51)	(-2.18)	(-1.38)	(-2.52)	(-2.21)	(-1.22)
$HIndex_t$	0.745	1.033	0.820	0.743	1.038	0.826
	(2.42)	(3.60)	(2.77)	(2.41)	(3.61)	(2.79)
$HIndex^2_t$	-0.673	-0.946	-0.902	-0.671	-0.949	-0.904
	(-2.30)	(-3.22)	(-2.95)	(-2.29)	(-3.23)	(-2.95)
$InstOwn_t$	-0.065	-0.038	-0.040	-0.066	-0.038	-0.030
	(-1.58)	(-1.01)	(-0.93)	(-1.61)	(-1.01)	(-0.69)
$Analyst_t$	0.012	0.022	-0.008	0.012	0.022	-0.002
	(0.93)	(1.91)	(-0.60)	(0.93)	(1.90)	(-0.18)
$Spread_t$	6.328	5.958	0.233	6.331	5.947	0.213
	(8.24)	(9.69)	(0.36)	(8.24)	(9.66)	(0.33)
Fixed Effects	FY	FY	FY	FY	FY	FY
Observations	36,782	36,782	36,782	36,782	36,782	36,782
R^2_{Adj}	45.43%	55.83%	74.82%	45.42%	55.79%	74.81%

Internet Appendix 7

Additional tests based on Thomson Reuters News Analytics data

This table presents regressions of corporate innovation outcome variables on additional news coverage measures estimated by incorporating the Thomson Reuters News Analytics (TRNA) data, including other control variables and unreported firm- and year-fixed effects (*FY*). The corporate innovation outcome variables are the log values of the average number of citations per patent (*CitaPat*), the summed value of patents scaled by market value of equity (*PValue*), and the number of patents (*Patent*) measured in year *t+2*. News coverage measures are the number of news articles extracted from TRNA database ($News_{TRNA}$), the number of news articles extracted from RavenPack database and if zero, then complemented by TRNA data ($News_{TRNA + RavenPack, 1}$), and sum of the number of news articles from both RavenPack and TRNA databases ($News_{TRNA + RavenPack, 2}$) estimated in year *t*. The full panel sample comprises 36,782 firm-year observations for news coverage variables from 2000 to 2010 and innovation outcome variables from 2002 to 2012. From M1 to M6, the sample period for news coverage variables spans from 2003 to 2010 because the TRNA data is only available from 2003. Variable definitions are detailed in the Appendix. Key results are highlighted in bold. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering.

	Year ~ [2003, 2010]						Year ~ [2000, 2010]		
	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$	$CitaPat_{t+2}$	$PValue_{t+2}$	$Patent_{t+2}$
Variable	M1	M2	M3	M4	M5	M6	M7	M8	M9
$News_{TRNA\ t}$	**-0.025**	**-0.061**	**0.004**						
	(-3.58)	**(-5.03)**	**(0.26)**						
$News_{TRNA + RavenPack, 1, t}$				**-0.029**	**-0.074**	**-0.055**			
				(-3.00)	**(-4.85)**	**(-2.91)**			
$News_{TRNA + RavenPack, 2, t}$							**-0.026**	**-0.063**	**-0.020**
							(-4.51)	**(-8.36)**	**(-2.69)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	FY	FY	FY	FY	FY	FY	FY	FY	FY
Observations	26,813	26,813	26,813	26,813	26,813	26,813	36,782	36,782	36,782
R^2_{Adj}	37.32%	45.49%	70.92%	37.27%	45.20%	70.98%	45.42%	56.50%	74.79%