Journal of Financial Economics 140 (2021) 815–837

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Negative peer disclosure[☆]

Sean Shun Cao[a], Vivian W. Fang[b,*], Lijun (Gillian) Lei[c]

[a] J. Mack Robinson College of Business, Georgia State University, 35 Broad St NW, Atlanta, GA 30303, USA
[b] Carlson School of Management, University of Minnesota, 321 19th Ave S, Minneapolis, MN 55455, USA
[c] Bryan School of Business and Economics, University of North Carolina at Greensboro, 516 Stirling St, Greensboro, NC 27412, USA

ARTICLE INFO

Article history:
Received 24 October 2019
Revised 28 May 2020
Accepted 29 May 2020
Available online 9 February 2021

JEL classifications:
G14
L1
M41
O30

Keywords:
Peer disclosure
Spillover
Product market rivalry
Technology proximity
Social media

ABSTRACT

This paper provides first evidence of negative peer disclosure (NPD), an emerging corporate strategy to publicize adverse news of industry peers on social media. Consistent with NPDs being implicit positive self-disclosures, disclosing firms experience a two-day abnormal return of 1.6–1.7% over the market and industry. Further exploring the benefits and costs of such disclosures, we find that NPD propensity increases with the degree of product market rivalry and technology proximity and disclosing firms outperform nondisclosing peers in the product markets in the year following NPDs. These results rationalize peer disclosure and extend the scope of the literature beyond self-disclosure.

1. Introduction

Corporate disclosure has always been a central topic of discussion among regulators, practitioners, and academics, as it plays a critical role in influencing product and financial markets. A vast literature has grown on disclosure for nearly four decades, with the predominant focus being "self-disclosure," that is, where a firm discloses its own information. Firms, however, do not operate in a vacuum. With fast-changing markets thanks to advances in technology, deregulations, and globalization, no modern firms escape rivalry. Might rivalry motivate firms to also issue "peer disclosure," that is, where a firm explicitly discloses information about its industry peers? Casual anecdotes suggest that some firms do publicize adverse news of industry peers on social media, a disclosure strategy that we label "negative peer disclosure" (hereafter NPD), but empirical evidence is absent. This paper makes the first attempt to systematically study the incentives and capital market effects of corporate NPDs.

☆ We are grateful for helpful comments from one anonymous referee, Bill Schwert (the editor), Cyrus Aghamolla, Alan Benson, Phil Berger, Beth Blankespoor, Ed deHaan, Shane Dikolli, Alex Edmans, Fabrizio Ferri, Ilan Guttman, Iftekhar Hasan, Mirko Heinle, Allen Huang, Gerry Hoberg, Xu Jiang, Jinhwan Kim, S.P. Kothari, Charles Lee, Tim Loughran, Hai Lu, Russ Lundholm, Josh Madsen, Mark Maffett, Iván Marinovic, Ken Merkley, Jim Naughton, Doug Skinner, Rodrigo Verdi, Wenyu Wang, Michael Weisbach, T.J. Wong, Gaoqing Zhang, Dexin Zhou, and Christina Zhu. This paper also benefited from comments by seminar participants at Tsinghua University, the University of Houston, the US Securities and Exchange Commission, and the Applied Econ Workshop Series at the University of Minnesota, and conference participants at the 2020 MFA meeting, the 2020 FARS Meeting, the 2020 CAFR Fintech Research Workshop at the ASSA Meeting, the 3rd Conference on Intelligent Information Retrieval in Accounting and Finance, the 2019 UVA Darden Accounting Mini-Conference, and the 2019 Stanford Accounting Summer Camp. We are grateful to Kenneth French for sharing US research returns data, Gordon Philips and Gerry Hoberg for sharing the TNIC industry classification data, Xuan Tian for sharing US patent data through 2014, and Xinyuan Shao and Yifan Yan for excellent research assistance.

* Corresponding author.
E-mail addresses: scao@gsu.edu (S.S. Cao), fangw@umn.edu (V.W. Fang), l_lei2@uncg.edu (L. (Gillian) Lei).

https://doi.org/10.1016/j.jfineco.2021.02.007

We build a sample of NPDs by crawling corporate Twitter pages.[1] Given the focus on negative peer disclosures, we tailor our search to ensure that a Twitter message, "tweet," contains only adverse news of the tweeted firm(s) and that the tweeting and tweeted firm(s) are industry peers. We form pairs of peer firms using the Text-Based Network Industry Classifications (TNIC) system of Hoberg and Phillips (2010, 2016, hereafter HP) and capture the tone of a tweet—tweeting firm's summary of the news—using the financial dictionary of Loughran and McDonald (2011). It is crucial to exclude tweets also containing direct information about tweeting firms so we can more confidently attribute capital market effects, if any, to these firms' NPDs rather than their self-disclosures. These stringent criteria lead to our cleanest and most homogenous sample, which comprises 649 corporate tweets.[2] We use it as the primary sample in the analyses below.

As a representative example of this sample, Globalscape, Inc., a Texas-based software developer, tweeted a news article about Dropbox, Inc. and Box, Inc. on May 19, 2014. This example reflects the two features of NPDs that we intend to capture. First, the news tweeted by Globalscape is evidently adverse for Dropbox and Box: it covers a major vulnerability in the online platforms of Dropbox and Box that allows third-party websites to access clients' private files, and its headline reads " Dropbox and Box leak files in security through obscurity nightmare." Second, Dropbox and Box specialize in file hosting service, and Globalscape derives a large majority of its revenues from enterprise software products such as managed file transfer and information security, making them product market rivals. The Online Appendix lists the details of this example and additional examples of NPDs in our sample.

Our analysis opens by providing an overview of the primary sample. Four findings bear emphasis. First, consistent with Twitter becoming a popular platform for corporate disclosure, NPD frequency generally increases over time. Second, NPDs are almost exclusively linked to product market news of technology (tech) firms, often covering defects of tech peers' products and services. Third, NPDs appear to be reactionary—as they are mostly rebroadcasts of news from other sources—but unlikely impulsive—as they are tweeted from professionally managed corporate Twitter accounts typically during regular work hours. Additionally, we find no evidence of tweeting firms timing NPDs to be near their own major information events. Fourth, tweeting firms are younger, smaller, and less profitable than tweeted firms but are more efficient in generating sales and hold more cash-to-assets and less debt-to-assets. The two groups of firms exhibit similar levels of market-to-book, investment, advertising spending, and momentum. Although less established than tweeted firms, tweeting firms are larger and valued much higher than the average publicly traded tech firm.

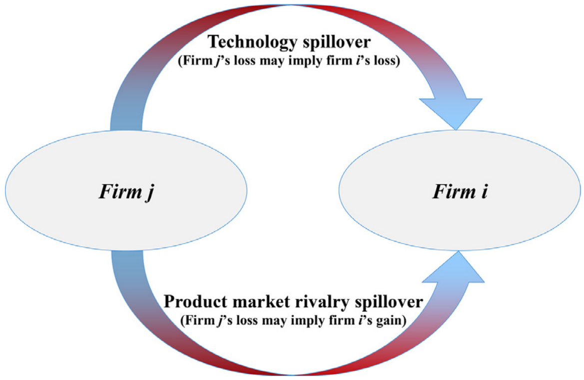

Fig. 1. Possible spillover effects from peer tech firms' adverse news. This figure depicts the two possible spillover effects from firm *j*'s adverse news on firm *i*. We label firm *i* the focal firm, which decides whether to issue NPD upon receiving the news, and firm *j* the peer firm. The product market rivalry spillover arises because the adverse news of firm *j* may positively affect firm *i* due to prospects of business stealing. The technology spillover arises because the news may negatively affect firm *i* due to possible inferences about common technology failures.

We next probe firms' incentives for issuing NPDs. Our main hypothesis is that NPDs are tweeting firms' implicit self-disclosures that provide new, positive information about themselves. Under this "disclosure hypothesis," the classic benefit-cost framework applies.

The benefits of issuing NPDs are tied to the spillover effects formalized by Bloom et al. (2013, hereafter BSV). Using the earlier example to illustrate these benefits, the adverse news of Dropbox and Box may positively affect Globalscape because they are rivals—the "product market rivalry spillover" in BSV. At the same time, the news of Dropbox and Box may negatively affect Globalscape if it allows one to infer a common technology failure—the "technology spillover" in BSV.[3] Fig. 1 depicts the two spillover effects. By publicizing the news of Dropbox and Box via an NPD, Globalscape signals confidence that its own platform is not exposed to the same technology vulnerability; this new information may benefit Globalscape by strengthening the positive effect from the rivalry spillover and counteracting the negative effect from the technology spillover. Thus, we expect firms to have greater incentives to issue NPDs about peers with which they have closer product market rivalry and technology proximity because disclosure benefits are higher.

[1] Twitter is an online news and social networking site. We focus our study on Twitter for three reasons. First, Twitter is popular among US corporations. Second, Twitter messages are restricted to 140 characters (280 characters after November 7, 2017) and are thus succinct and focused compared to messages posted on other social media sites. Third, Twitter allows web crawling, while other social media sites typically prohibit it.

[2] Additionally, it is difficult to perform textual analysis on tweets also containing direct information about tweeting firms because these tweets supposedly reflect a positive tone toward tweeting firms but a negative tone toward tweeted firms. Section 2 provides further rationale for our sampling criteria. For example, we do not study nonnegative peer disclosures or benchmark NPDs against them in our main analyses because they are highly heterogeneous and difficult to generalize. Nevertheless, we acknowledge that our primary sample likely underestimates the incidence of corporate NPDs. Section 5 presents similar results using a larger but less homogenous sample.

[3] Neither spillover is positive or negative per se; the main distinction between them is that the rivalry spillover affects two peer firms in the opposite direction, while the technology spillover affects them in the same direction.

The costs of issuing NPDs are more subtle—NPDs posted on public social media sites like Twitter are fully transparent, so disclosing firms should rationally anticipate increased scrutiny from product market rivals, consumers, and other market participants. Disclosure costs help explain why corporate NPDs are not cheap talk or widespread, as they may backfire and lead to monetary and reputation loss if disclosing firms are later revealed to suffer from the same issues that they tweeted about.[4] Thus, we expect firms of higher quality to have greater incentives to issue NPDs because they can better withstand scrutiny and thus have lower disclosure costs.

An alternative hypothesis is that NPDs merely diffuse the information about tweeted firms from the initial news—the "dissemination hypothesis." The two hypotheses have different implications for the market reaction. The disclosure hypothesis predicts positive returns to tweeting firms surrounding NPDs as these firms release new, positive information about themselves. Under the dissemination hypothesis, if the market could not fully absorb the initial news (e.g., due to some investors' limited attention as in Hirshleifer and Teoh, 2003), we expect returns to tweeting/tweeted firms surrounding NPDs to be similar to those surrounding the initial news, only to a lesser degree. The two hypotheses also have different predictions for the relation between NPD propensity and the strength of technology spillover: While a firm has incentives to release new, positive information via an NPD to counteract the negative effect from the technology spillover (the disclosure hypothesis), it should not seek to amplify this effect without adding new information (the dissemination hypothesis).

We first examine event returns to NPDs. Results show that during the two-day event window (i.e., the day of NPD and the day after), tweeting firms enjoy an excess return of 1.6% over the return on an equal- or value-weighted market portfolio and an excess return of 1.7% (1.6%) over the return on an equal- (value-) weighted industry portfolio; the average two-day gain is \$34.9–\$53.2 million. Importantly, tweeting firms' returns surrounding NPDs are much larger than their returns surrounding initial news days, which is consistent with these firms releasing new information via NPDs. Further, while tweeted firms, on average, exhibit small negative returns surrounding initial news days, their returns surrounding NPD days are largely insignificant. Results are similar if we compute the excess returns over benchmark returns on the Fama-French characteristic-based portfolios. Combined, these results are more consistent with the disclosure hypothesis than the dissemination hypothesis.

Further exploring the benefits of NPDs, we find that NPD propensity increases with the strength of product market rivalry spillover and technology spillover between the tweeting and tweeted firms. A one standard deviation increase in the product proximity measure of BSV (the product similarity measure of HP) is associated with a 1.7% (2.5%) increase in the probability of NPDs conditional on the occurrence of the tweeted firm's adverse news, 23% (34%) of the sample mean. A one standard deviation increase in the technology proximity measure of BSV is associated with a 4.1% increase in the conditional probability of NPD, 56% of the sample mean. Further, the disclosing firm, on average, enjoys a more positive market reaction to its NPD when spillover links are stronger.

We also examine the relation between NPD propensity and the clarity of spillover links. Results show that a firm is more likely to issue an NPD when its peer relationship with the firm having adverse news is less clear to the market, and the disclosing firm enjoys a more positive market reaction to its NPD. The relation between NPD propensity and the strength and clarity of spillover links is robust to including various controls and fixed effects and to using alternative dictionaries to capture disclosure tone, alternative measures of spillover strength, and a less homogenous sample of larger size. These results shed light on the existence of spillover effects and firms' capability of internalizing spillovers. Again, they are more consistent with the disclosure hypothesis, particularly the finding of a positive relation between NPD propensity and technology spillover.

Finally, we find that NPD tweeting firms outperform non-NPD-tweeting peers with similar pre-event characteristics in product markets: The increase in industry-adjusted sales growth, market share growth, and sales contract growth from the year before NPD to the year after is 25.7, 1.9, and 74.3% higher for NPD tweeting firms than for matched non-NPD-tweeting peers, respectively. NPD tweeting firms also exhibit better operating performance, as their increase in return-on-assets and cash flow-to-assets is 3.6 and 2.3% higher than non-NPD-tweeting peers, respectively. These differences remain if we control for more firm characteristics and fixed effects. Surrounding tweeting firms' NPDs, their matched non-NPD-tweeting peers do not exhibit any positive returns. The finding that better-performed firms are more likely to issue NPDs sheds light on the costs of such disclosures.

To our best knowledge, this is the first study to show explicit corporate NPDs and the first to examine the incentives and capital market effects of this disclosure strategy. To be sure, the behavior of spreading negative information about competitors does exist in other settings. Marketing research labels this behavior "comparative advertising" and focuses on studying its effectiveness in promoting sales.[5] Political science labels this behavior "negative campaigning" (see Lau and Rovner, 2009 for a review). Our setting

[4] Disclosure costs also help explain why firms may prefer implicit NPDs over explicit self-disclosures. Compared with NPDs, a firm's explicit positive self-disclosures about its own products that also bash competitors likely need legal review and approval as explicit disclosures arguably subject the firm to closer scrutiny and possibly litigation risk. For example, the Volkswagen Group paid a hefty price for its emissions scandal. For years, Volkswagen asserted that its diesel cars were more eco-friendly than the competing brands and built a consumer base via this claim, which turned out to be not credible. Upon revelation, the scandal triggered over 100,000 tweets from angry customers and several trending hashtags directed at the company in addition to monetary costs (see Vanitha Swaminathan and Suyun Mah, "What 100,000 tweets about the Volkswagen scandal tell us about angry customers," Harvard Business Review, September 2, 2016).

[5] Prominent theories and recent studies of comparative advertising include Anderson and Renault (2009), Barigozzi et al. (2009) and Anderson et al. (2016).

offers a unique opportunity to assess the capital market effects of NPDs in an event study by separating information spillovers from direct information effects. This is difficult to achieve in other settings: Comparative advertising and negative campaigning often use a combination of attack and contrast techniques, thus carrying both direct information effects and spillover effects.

This study also extends the disclosure literature in three ways. First, it provides first evidence of peer disclosure, while much of the literature is dedicated to studying self-disclosure (see Beyer et al., 2010 for a recent review).[6] Second, it establishes spillovers in a novel way. Prior studies show that firms' self-disclosures have spillover effects on peer firms (Foster, 1981; Freeman and Tse, 1992) and firms factor in these effects in their self-disclosures (Aobdia and Cheng, 2018; Kim et al., 2020). We approach spillover effects from a different angle: Since NPDs are responses to peer firms' news, they are most likely driven by spillover effects. Finally, it adds to the growing literature on the dynamic nature of corporate disclosure in the era of social media (Miller and Skinner, 2015; Blankespoor, 2018). NPDs, likely a product of social media, would be difficult to engage with traditional disclosure methods. While the US Securities and Exchange Commission (SEC) just began to accept and regulate firms' use of social media to disclose their own information, peer disclosures are generally overlooked and left unregulated. Our research highlights the potential importance of peer disclosure and the need for regulatory attention.[7]

2. Data and sample

We build the primary sample of NPDs used in our analysis in four steps. First, we form pairs of peer firms by intersecting the Compustat annual files with HP's TNIC data. To compile this data, HP perform text-based analysis of product descriptions in 10-K filings for any given pair of firms in a year and define peer firms based on their product similarity in the year. Given our focus on peer disclosure, the pairwise, time-varying TNIC system is more suitable than other industry classification systems such as the Standard Industrial Classification (SIC) system and the North American Industry Classification System (NAICS), both of which evolve slowly in response to product market developments. We define pairs of peer firms at the TNIC-3 level, which is comparable to the three-digit SIC level in coarseness.

Second, for every firm assigned to a pair, we visit its corporate website and search for a corporate Twitter account. If multiple accounts are listed (e.g., for different branches or lines of products), we use the one that represents the entire firm or corporate headquarter. Once we locate such an account, we link to the Twitter site to ensure that the account is indeed maintained by the firm. We manually search for a firm's Twitter account if we cannot locate it on the corporate website and if one exists, we assess its authenticity. This step yields an initial sample of 177,355 unique pairs of peer firms and 2117 unique firms with verified Twitter accounts. The sample period is from 2009, the year marking the beginning of considerable corporate presence on Twitter, to 2017, the last year of the TNIC data.

Third, we search for peer disclosures issued between each of the 177,355 firm pairs. To capture peer disclosures, for a given pair of firm *i*-*j*, we first submit a query to firm *i*'s Twitter site to collect tweets that mention firm *j* but not firm *i* and then a parallel query to firm *j*'s Twitter site to collect tweets that mention firm *i* but not firm *j*. We limit both queries to be between June 1, 2008 (the earliest possible date for fiscal year 2009) and May 31, 2018 (the latest possible date for fiscal year 2017), as Compustat defines. In setting the queries, we match firms using names as spelled in their Twitter accounts/handles, as fuzzy matches using ticker symbol or company name yield a high false positive rate. We further require all tweets to contain a hyperlink, which allows us to trace the source of the news. These steps yield a sample of 9706 peer disclosure tweets posted between 2019 firm pairs.

Fourth, we classify peer disclosure tweets, often brief summaries of the underlying news, based on tone. We deem the tone of a tweet negative (positive) if the news summary contains more negative (positive) words than positive (negative) words, with both word lists defined following Loughran and McDonald (2011). Tweets that contain equal amounts of positive and negative words and tweets that contain neither are deemed neutral. By defining tone based on the news summary, we directly capture the sentiment that a tweeting firm expresses in its disclosure about the peer firm.[8] Of the 9706 tweets, we retain only the 891 tweets that exhibit a negative tone, reflecting our goal to study NPDs; excluded are 1405 tweets with a positive tone and 7410 neutral tweets.[9]

---

[6] Our study is particularly related to two streams of disclosure research. The first stream studies the incentives and capital market effects of negative self-disclosures (e.g., Skinner, 1994, 1997; Aboody and Kasznik, 2000), and we study those of NPDs. The second stream studies the effect of product market competition on self-disclosures (e.g., Ali et al., 2014; Cao et al., 2018), and we study the effect on NPDs.

[7] Social media has opened up new opportunities for corporate disclosure (Blankespoor et al., 2014; Lee et al., 2015; Cade, 2018; Crowley et al., 2018; Jung et al., 2018; Rakowski et al., 2021). It has also raised regulatory challenges. In a 2013 press release, the SEC stated that firms may announce material information to investors on social media but must first alert investors about the media they plan to use and ensure that the media is publicly accessible and nonexclusive (Section 2013–51).

[8] We define tone based on the news summary in an NPD rather than the news itself for three reasons. First, news may be interpreted and framed in different ways. Given the same news, a negative disclosure could "rub salt in the wound," but a positive disclosure may "soften the blow." In other words, how firms disclose peer firms' news may reveal information about their relationship that is incremental to the news. Second, dimension reduction is recommended in textual analysis (Loughran and Mcdonald, 2014, 2016; Gentzkow et al., 2019). In this context, applying the "bag-of-words" approach to capture disclosure tone from a summary of the news article rather than the full text reduces noise and increases precision, as manual summaries are essentially supervised dimension reductions in textual analysis. Third, a nontrivial amount of news articles from earlier years are missing, making it difficult to trace them. In later analyses, we show that the market reaction to tweeted firms surrounding initial news days is, on average, negative within the subsample of NPDs for which we can trace the initial news articles, confirming the adverse nature of such news.

[9] Compared with NPDs, positive and neutral peer disclosures are highly heterogeneous, in terms of both news type and industry distribution.

Fig. 2. Word cloud of NPDs. This figure depicts a word cloud based on the frequency of the negative words appeared in our primary sample of NPDs. The sample comprises 649 tweets posted by corporate Twitter accounts between fiscal year 2009 and 2017. We define a tweet negative peer disclosure (NPD) if the tweeting firm discloses news of its industry peer(s) without mentioning itself and the disclosure contains more negative words than positive words according to the financial dictionary of Loughran and McDonald (2011).

Within the 891 tweets, we manually check those mentioning firms with meaningful English words in their names (e.g., Box, Express, and Guess) and delete those mentioning Twitter and Facebook in contexts unrelated to news of the two firms (e.g., Facebook fan, Facebook page, and Twitter chat) and no other firms. The final sample of NPDs, requiring tweeting firms to have financial and trading data, includes 649 tweets posted between 2009 and 2017. In the analyses below, we refer to this sample as our primary sample of NPDs. Fig. 2 presents a word cloud for the negative words used in this sample.

3. Descriptive statistics

This section provides initial evidence of corporate NPDs issued on Twitter. Section 3.1 reports sample distribution of tweets, and Section 3.2 describes characteristics of the tweeting and tweeted firms. Detailed variable definitions are provided in Appendix A.

3.1 Tweets

Table 1, Panel A reports distribution by year for the primary sample. Two patterns emerge. First, the frequency of NPDs generally increases over time. Of the 649 NPDs, nearly three quarters (459 events or 71%) occurred in 2013–2017, the last five years of the nine-year sample period. Second, the temporal increase in NPDs is not monotonic: 2014 and 2016 have the highest incidence, with 123 and 114 events (19% and 18%), respectively. Although the patterns are consistent with firms' increasing use of Twitter to communicate, we do not intend to conjecture the overall incidence of NPDs in a year, as it also depends on the occurrence rate of peer firms' adverse news.

Table 1, Panel B reports distribution by industry for the primary sample. We sort NPDs into industries based on tweeting firms' four-digit SIC codes because TNIC, as a peer-to-peer classification system, forms a unique industry for each firm every year, making it infeasible to sort firms into industries. As shown, NPDs predominantly originate from tech firms. "Computer Programming and Data Processing" and "Prepackaged Software" have the highest incidence of 46% and 28%, respectively. This result is consistent with tech firms being early adopters and avid users of social media.

Table 1, Panel C reports distribution by news type for the primary sample. The vast majority of NPDs in our sample (611 events or 94%) cover product-market-related news. Of these events, 458 (75%) discuss peer firms' products (e.g., features, defects, and new developments), and the rest cover various types of news related to peer firms' product strategy, market competition, industry outlook, regulations, lawsuits, and top talent turnover. We retain the 38 nonproduct-market-related NPDs in our analyses, but removing them does not affect our results throughout.

The first three panels of Table 2 shed light on the news sources of NPDs and tweeting patterns. Most of the NPDs in our sample are retweets of news from a different source. Panel A lists the top ten news sources for the 376 NPDs that we are able to trace the initial news days; all are tech oriented except for Forbes.[10] Panel B reports the number of days between the initial news day and the NPD day for this subsample: 165 (44%) are retweeted on the same day of the initial news day, an additional 149 (40%) are retweeted within three days of the initial news day, and the rest are retweeted more than three days later. The mean (median) delay between the initial news day and the NPD day is seven days (one day). Panel C reports the sample distribution based on the tweeting time for the primary sample. Six hundred and one tweets (93%) fall on workdays, of which 353 (59%) are posted during the regular US work hours, which are assumed to be 9 am–6 pm in local time of the corporate headquarter. Table OA1 of the Online Appendix reports sample distribution based on tweeting time relative to market open. Fifty percent of the NPDs are posted during regular trading hours (9:30 am–4 pm), and 25% are posted during normal extended trading hours (8–9:30 am and 4–6:30 pm), all in Eastern Time. These results, combined with the fact that corporate Twitter accounts are typically managed by investor relation professionals (Blankespoor et al., 2014), suggest that corporate NPDs are unlikely impulsive.

Based on manual reviews of two random samples of 100 each, we find it difficult to ascertain how tweeting and tweeted firms of nonnegative peer disclosures are related. Even if tweeting and tweeted firms do not appear to be affiliated at the time of the disclosure, they may plan to form a relationship in the future. It is thus hard to generalize tweeting firms' ex ante incentives for issuing nonnegative disclosures and hard to predict how the market would react to them. For this reason, we exclude nonnegative peer disclosures from our main analyses.

[10] This analysis excludes 200 NPDs for which we cannot trace the initial news days either because the hyperlink in the tweet is broken or because the date is unspecified as well as 73 NPDs initiated by the disclosing firms themselves.

Table 1
Sample distribution of NPDs on Twitter.

Panel A: By year (N = 649)		
Year	Number of NPDs	Percentage of NPDs (%)
2009	25	3.85
2010	55	8.47
2011	54	8.32
2012	56	8.63
2013	84	12.94
2014	123	18.95
2015	70	10.79
2016	114	17.57
2017	68	10.48
Total	649	100.00
Panel B: By industry (N = 649)		
Industry group (four-digit SIC level)	Number of NPDs	Percentage of NPDs (%)
Computer Programming and Data Processing	302	46.52
Prepackaged Software	183	28.19
Communications Services	34	5.25
Business Service	14	2.15
Semiconductors	10	1.54
Radiotelephone Communications	11	1.70
Computer Communications Equipment	10	1.54
Computer Integrated Systems Design	9	1.39
Computer Processing & Data Preparation	8	1.23
Computer Peripheral Equipment	7	1.08
Other	61	9.41
Total	649	100.00
Panel C: By news type (N = 649)		
News type	Number of NPDs	Percentage of NPDs (%)
Product market related		
Features, defects, developments of products	458	70.57
Product and corporate strategy	59	9.09
Market conditions and industry outlook	56	8.63
Regulations and lawsuits	28	4.31
Top talent turnover	10	1.54
Subtotal	611	94.14
Other		
Financial and stock market performance	33	5.08
Miscellaneous	5	0.46
Total	649	100.00

Panel A reports sample distribution by fiscal year of the tweeting firm, Panel B reports sample distribution by primary four-digit SIC industry code of the tweeting firm, and Panel C reports sample distribution by news type. The sample comprises 649 tweets posted by corporate Twitter accounts between fiscal year 2009 and 2017.

Panel D examines whether firms strategically time the release of their NPDs using the primary sample. A study of NPDs' capital market effects would be more convincing if these disclosures are less confounded by other information events. We focus on quarterly earnings announcements and code an indicator to denote whether a firm's NPD falls in a small window surrounding a quarterly earnings announcement. We compare the sample average of this indicator to a hypothetical benchmark assuming a uniform distribution of NPDs. For three windows of [-3, +3], [-2, +2], and [-1, +1] with 0 being the earnings announcement day, the proportion of our sample NPDs occurring within the window is insignificantly different from the benchmark. That is, we find no evidence of firms strategically timing NPDs to be near their own major information events. This result suggests that firms' decisions to tweet adverse news of peer firms are reactionary to the news occurring.

3.2 Tweeting firms and tweeted firms

Table 3, Panel A lists the top ten tweeting and tweeted firms in the primary sample. Both sets of firms are tech oriented, with tweeted firms appearing more established than tweeting firms. All top ten ranked tweeted firms are among the world's 2000 largest public companies (Forbes 2019 Global 2000 list), and eight of them are leaders in their respective industries. In contrast, Symantec Corp is

Table 2
Issuance patterns of NPDs on Twitter.

Panel A: Top ten news sources ($N = 376$)

Rank	News source	Number of NPDs originated
1	Naked Security	31
2	CNET	27
3	Computerworld	22
4	ZDNet	16
5	PCWorld	14
6	Mashable	11
7	Forbes	10
8	DarkReading	8
9	Krebs on Security	8
10	Fierce Wireless	8

Panel B: Days between the initial news day and the NPD day ($N = 376$)

Number of days	Number of NPDs	Percentage of NPDs (%)
0	165	43.88
1–3	149	39.63
4–10	38	10.11
11–20	11	2.93
21–31	6	1.60
31–90	2	0.53
>90	5	1.33
Total	376	100.00
Mean=7 (Median=1)		

Panel C: Time of tweeting ($N = 649$)

Time of tweeting (in the local time of corporate headquarter)	Workdays		Weekends and holidays	
	Number of NPDs	Percentage of NPDs (%)	Number of NPDs	Percentage of NPDs (%)
12:00 AM to 8:59 AM	68	11.31	5	10.42
9:00 AM to 6:00 PM	353	58.74	32	66.66
6:01 PM to 11:59 PM	180	29.25	11	22.92
Total	601	100.00	48	100.00

Panel D: NPDs surrounding quarterly earnings announcements ($N = 649$)

Window	[−3,+3]	[−2,+2]	[−1,+1]
(a)% of NPD tweeting	7.88%	6.21%	3.94%
(b) Benchmark% of NPD tweeting	7.69%	5.49%	3.30%
z-stat of testing (a)=(b)	0.182	0.814	0.920

Panel A lists the top ten news sources in the sample and the number and percentage of NPDs originated from these news sources. Panel B reports the sample distribution of the number of days between the initial news day and the NPD day. Panel C reports the sample distribution of the tweeting time, logged as of the local time of corporate headquarters. Panel D reports (a) the proportion of the sample NPDs that occur within the window of $[-n, +n]$ with 0 denoting the quarterly earnings announcement day, (b) a benchmark percentage calculated assuming a uniform distribution of NPDs, and z-statistics of testing whether (a) equals (b). Panels C-D use the primary sample, which comprises 649 tweets posted by corporate Twitter accounts between fiscal year 2009 and 2017. Panels A-B use the subsample of 376 NPDs for which we are able to trace the initial news source and date.

the only top ten tweeting firm on the Forbes 2019 Global 2000 list, and none are industry leaders.[11]

Table 3, Panel B reports summary statistics of the 228 unique tweeting firm-years and 164 unique tweeted firm-years in the primary sample. Consistent with tweeting firms being less established than tweeted firms, tweeting firms are listed more recently (16 versus 26 years), smaller in terms of market capitalization (7 versus 10.2 in natural logarithm) and assets (6.7 versus 9.7 in natural logarithm), and less profitable (with a return-on-assets of -0.03 versus 0.04). They, however, hold more cash (with a cash-to-assets of 0.33 versus 0.29) and less debt (with a debt-to-assets of 0.13 versus 0.18) and are more efficient in generating sales than tweeted firms (with an asset turnover of 0.8 versus 0.6); all are quoted using the mean values. The two sets of firms exhibit similar levels of market-to-book, capital expenditures, research and development (R&D) ex-

[11] Forbes's Global 2000 list is available at https://www.forbes.com/global2000. This list takes into account four metrics: Sales, profit, assets, and market value. Industry leaders refer to the top ten ranked firms within an industry. Separately, we cross-check with competitor analysis websites (CSIMarket.com and Gartner Peer Insights) to verify that firms tweeted by our two top tweeting firms, Support.com, Inc. and Symantec Corp, are indeed their competitors along at least one product/ service line. We also verify that NPDs issued by TheStreet, Inc. in our sample are negative tweets about competing news websites such as Microsoft Bing and Twitter.

Table 3
Descriptive statistics of tweeting and tweeted firms.

Panel A: Top ten tweeting and tweeted firms

Rank	Tweeting firm	Number of NPDs	Tweeted firm	Number of NPDs
1	Support.com, Inc.	122	Microsoft Corp	168
2	Symantec Corp	98	Facebook, Inc.	83
3	The Street, Inc.	75	Adobe Inc.	74
4	Imperva, Inc.	32	Verizon Communications Inc.	72
5	Qualys, Inc.	21	Twitter, Inc.	56
6	Boingo Wireless, Inc.	20	Cisco Systems, Inc.	36
7	Palo Alto Networks, Inc.	13	Oracle Corp	32
8	Towerstream Corp	12	Intel Corp	9
9	Carbonite, Inc.	11	Symantec Corp	9
10	T-Mobil US, Inc.	9	IBM Corp	8

Panel B: Comparison of tweeting firms, tweeted firms, and technology firms

Variable	(1) Tweeting firm-years ($N = 228$)	(2) Tweeted firm-years ($N = 164$)	(3) Technology firm-years ($N = 5091$)	(4) (1) – (2)	(5) (1) – (3)	(6) (2) – (3)
Age	15.811	25.652	17.735	−9.841***	−1.924**	7.917***
Size	6.995	10.234	6.188	−3.239***	0.807***	4.046***
Asset	6.659	9.708	5.554	−3.049***	1.105***	4.154***
MB	5.756	4.982	3.772	0.774	1.984***	1.210*
ROA	−0.027	0.042	−0.290	−0.069***	0.263***	0.332***
Lev	0.130	0.177	0.191	−0.047***	−0.061***	−0.014
Cash	0.325	0.289	0.430	0.036*	−0.105***	−0.141***
Capex intensity	0.076	0.076	0.082	0.000	−0.006	−0.006
R&D intensity	0.127	0.115	0.970	0.012	−0.843***	−0.855***
Ad intensity	0.024	0.026	0.009	−0.002	0.015***	0.017***
Asset turnover	0.787	0.617	0.622	0.170***	0.165***	−0.005
Past year return	0.003	−0.007	−0.006	0.010	0.009	−0.001

Panel C: Pairwise comparison of tweeting and tweeted firms

	(1) Tweeting firm-years ($N = 619$)	(2) Tweeted firm-years ($N = 619$)	(3) (1)–(2)
Age	15.675	24.782	−9.107***
Size	6.689	11.349	−4.660***
Asset	6.374	10.727	−4.353***
MB	5.031	5.081	−0.050
ROA	−0.032	0.073	−0.105***
Lev	0.082	0.173	−0.091***
Cash	0.407	0.375	0.032***
Capex intensity	0.069	0.081	−0.012***
R&D intensity	0.123	0.140	−0.017***
Ad intensity	0.048	0.022	0.026***
Asset turnover	0.681	0.517	0.164***
Past year return	0.000	−0.003	0.003

Panel A lists the top ten tweeting and tweeted firms in the sample and the number of NPDs associated with these firms. Panel B reports summary statistics of firm characteristics for the 228 unique tweeting firm-years and 164 unique tweeted firm-years in the sample and for 5091 unique technology firm-years with corporate Twitter accounts in the Compustat database. Technology firms are defined as those with the four-digit SIC codes of 2833–2836, 3570–3577, 3600–3674, 7371–7379, or 8731–8734. Panel C reports summary statistics of firm characteristics for the unique 619 firm pair-years in the sample, where we log the 11 NPDs that mention two tweeted firms as 22 separate events. Column (3) tests whether the mean value of a firm characteristic in column (1) equals the corresponding value in column (2). Firm characteristics include firm age (*Age*); market value of equity in natural logarithm (*Size*); book value of assets in natural logarithm (*Asset*); market-to-book (*MB*); return-on-assets (*ROA*); debt-to-assets (*Lev*); cash-to-assets (*Cash*); capital expenditure-to-sales (*Capex intensity*); R&D expenditure-to-sales (*R&D intensity*); advertising expenditure-to-sales (*Ad intensity*); asset turnover (*Asset turnover*); and compounded market-adjusted monthly returns over the 12 months prior to the disclosure event or the fiscal year end (*Past year return*). Detailed variable definitions are in Appendix A. Panel A uses the primary sample, which comprises 649 tweets posted by corporate Twitter accounts between fiscal year 2009 and 2017. Panel B uses the samples of unique tweeting firm-years and tweeted firm-years derived from the primary sample with data available to calculate firm characteristics. Panel C uses the sample of unique firm pair-years derived from the primary sample with data available to calculate firm characteristics. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

penditures, advertising spending, and stock returns over the past 12 months.

We also benchmark both sets of firms against the tech firms, defined as those with the four-digit SIC codes of 2833–2836, 3570–3577, 3600–3674, 7371–7379, or 8731–8734 in the Compustat database following Files (2012) and corporate Twitter accounts. The average tech firm is older than the average tweeting firm but younger than the average tweeted firm. Compared with both the average tweeting firm and the average tweeted firm, the average tech firm is smaller, less profitable, and valued lower. It has larger cash holdings and makes more investment in R&D but advertises less.

Table 3, Panel C conducts a pairwise comparison of the tweeting and tweeted firms. This analysis includes 619 unique firm pair-years, after we require financial data to be available for both tweeting and tweeted firms and log the 11 NPDs that mention two tweeted firms as 22 separate events. Results are largely consistent with those in Panel B. The exceptions are that tweeting firms now exhibit a lower level of investment but a higher level of advertising than tweeted firms.

4. Main analyses

We consider two hypotheses in examining the incentives and capital market effects of corporate NPDs. The disclosure hypothesis posits that NPDs are tweeting firms' implicit positive self-disclosures about themselves. Such disclosures are motivated by the spillover effects from peer firms' adverse news: The product market rivalry spillover arises because the news may positively affect the firm due to prospects of business stealing, and the technology spillover arises because the news may negatively affect the firm due to possible inferences about common technology failures. An NPD, by releasing new, positive information about the disclosing firm, can strengthen the positive effect from the rivalry spillover and counteract the negative effect from the technology spillover. In contrast, the dissemination hypothesis posits that NPDs diffuse the information about tweeted firms from the initial news, implying that some frictions and/or behavioral constraints prevented the initial news from being fully absorbed by the market. This section provides four sets of analyses to test these hypotheses.

4.1 Event returns

We first study event returns to tweeting firms. Table 4, Panel A reports returns to tweeting firms surrounding NPD days. The sample includes 599 disclosing firm-trading days.[12] As the panel shows, an NPD tweeting firm, on average, enjoys an excess return of 0.9% over the equal-weighted market and industry portfolios and 0.8% over the value-weighted market and industry portfolios on the event day. The event day, labeled 0, is either the day of NPD or the first subsequent trading day if an NPD falls on a weekend or a holiday. The excess returns nearly double when we expand the event window to two days: The cumulative abnormal return (CAR) during [0, +1] is 1.6% over the equal- and value-weighted market portfolios and is 1.7% (1.6%) over the equal- (value-) weighted industry portfolio; all are significantly different from zero at the 1% level. In unreported analyses, we gradually expand the measurement window of event returns. CARs over [0, +2] are virtually unchanged from CARs over [0, +1], and we do not see any reversal in the market reaction up to ten trading days.

As a falsification test, we examine CARs over the two-day window immediately before the event. CARs over [-2, -1] are either statistically indistinguishable from zero or marginally negative. This result, coupled with the earlier finding that firms do not strategically time NPDs to be near their own major information events, increases confidence that the issuance of NPDs, rather than concurrent news of the disclosing firm, triggers the observed positive market reaction.

A positive market reaction to tweeting firms surrounding NPDs can be consistent with either the disclosure hypothesis (that tweeting firms release new, positive information about themselves) or the dissemination hypothesis (if information from the initial news of tweeted firms benefited tweeting firms through spillover effects and continues to benefit them when diffused via NPDs). We conduct several additional analyses to distinguish the two hypotheses.

Table 4, Panel B repeats the analysis in Panel A excluding NPDs retweeted on initial news days. CARs to tweeting firms over [0, +1] remain significantly positive and become slightly larger. These patterns are less consistent with the dissemination hypothesis than the disclosure hypothesis, because a drift from the initial news should supposedly diminish over time, whereas a market reaction to new, positive information may occur regardless of how long an NPD lags the initial news.

Table 4, Panel C reports event returns to tweeting firms surrounding initial news days. The sample includes 411 tweeting firm-trading days populated from 449 NPD tweets (including the ones initiated by tweeting firms) for which we are able to trace the initial news days. In this sample, tweeting firms, on average, experience positive returns on initial news days: For the two-day window [0, +1], the CAR is 0.7% (0.6%) over the equal- (value-) weighted market portfolio and 0.8% (0.6%) over the equal- (value-) weighted industry portfolio. Table 4, Panel D repeats this analysis excluding NPDs retweeted on initial news days. Returns reported in Panels C-D, even when positive, are much smaller than those reported in Panels A-B, which is more consistent with tweeting firms releasing new information via NPDs (the disclosure hypothesis) than them merely diffusing information from the initial news (the dissemination hypothesis).

One concern is that the observed event returns to tweeting firms may be explained by concurrent news of these firms' fundamentals (e.g., growth option, profitability, or investment). To alleviate this concern, we

[12] Specifically, 649 tweets correspond to 609 unique tweeting firm-days because a small number of tweeting firms issue multiple NPDs on the same trading day. We further delete 11 tweets posted by firms during the year of initial public offerings but before trading started, corresponding to 10 unique tweeting firm-days.

Table 4
Market- and industry-adjusted event returns to tweeting firms.

Panel A: Market- and industry-adjusted CARs to tweeting firms surrounding NPDs

Event window	CARs over the market portfolio Equal-weighted	CARs over the market portfolio Value-weighted	CARs over the industry portfolio Equal-weighted	CARs over the industry portfolio Value-weighted
[0, 0]	0.009***	0.008***	0.009***	0.008***
[0, +1]	0.016***	0.016***	0.017***	0.016***
[−2, −1]	−0.003	−0.003*	−0.002	−0.004**
No. of obs.	599	599	599	599

Panel B: Market- and industry-adjusted CARs to tweeting firms surrounding NPDs excluding same-day NPDs

Event window	CARs over the market portfolio Equal-weighted	CARs over the market portfolio Value-weighted	CARs over the industry portfolio Equal-weighted	CARs over the industry portfolio Value-weighted
[0, 0]	0.009***	0.009***	0.010***	0.008***
[0, +1]	0.017***	0.016***	0.018***	0.016***
[−2, −1]	−0.003	−0.003	−0.002	−0.005**
No. of obs.	411	411	411	411

Panel C: Market- and industry-adjusted CARs to tweeting firms surrounding initial news days

Event window	CARs over the market portfolio Equal-weighted	CARs over the market portfolio Value-weighted	CARs over the industry portfolio Equal-weighted	CARs over the industry portfolio Value-weighted
[0, 0]	0.003**	0.002*	0.003***	0.001*
[0, +1]	0.007***	0.006***	0.008***	0.006***
[−2, −1]	−0.001	−0.001	0.000	−0.001
No. of obs.	411	411	411	411

Panel D: Event returns to tweeting firms surrounding initial news days excluding same-day NPDs

Event window	CARs over the market portfolio Equal-weighted	CARs over the market portfolio Value-weighted	CARs over the industry portfolio Equal-weighted	CARs over the industry portfolio Value-weighted
[0, 0]	−0.002	−0.002	−0.001	−0.002*
[0, +1]	−0.001	−0.001	−0.000	−0.002
[−2, −1]	−0.001	−0.001	0.000	−0.002
No. of obs.	224	224	224	224

Panel A reports the mean market- or industry-adjusted cumulative abnormal returns (CARs) to tweeting firms surrounding NPDs. Panel B reports the corresponding CARs to tweeting firms surrounding NPDs excluding same-day NPDs (i.e., NPDs retweeted on initial news days). Panel C reports the corresponding CARs to tweeting firms surrounding initial news days. Panel D reports the corresponding CARs to tweeting firms surrounding initial news days excluding same-day NPDs. The first two columns of each panel report market-adjusted CARs, and the last two columns of each panel report industry-adjusted CARs. Each column tests whether the market- or industry-adjusted CAR is significantly different from zero. Detailed variable definitions are in Appendix A. Samples include individual NPD and initial news events for which market- and industry-adjusted CARs are available for tweeting firms as indicated in each panel. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

form characteristic-based portfolios using the Fama-French breakpoints downloaded from Kenneth French's data library and compute firms' CARs over equal- and value-weighted returns from these portfolios. Table 5 repeats the analyses in Table 4 using excess returns over benchmark returns on the univariate-sorted portfolios (i.e., CARs adjusted by book-to-market (BM), profitability, and investment). Samples include individual NPDs and initial news events for which characteristic-adjusted CARs can be computed for tweeting firms. We observe a similar pattern: Tweeting firms experience positive market reactions on the day of the NPD and the day after but not prior, and their returns are higher surrounding NPDs than initial news days. Table OA2 of the Online Appendix reports similar results using excess returns over benchmark returns on the bivariate-sorted portfolios (i.e., CARs adjusted by BM and profitability, BM and investment, and profitability and investment).

We next study event returns to tweeted firms. Table 6, Panel A reports returns to tweeted firms surrounding initial news days. The sample includes 388 tweeted firm-trading days populated from the subsample of 449 NPD tweets used in Table 4, Panel C. Despite a small sample, we observe negative excess returns to tweeted firms surrounding initial news days and insignificant or positive returns prior to the news. CARs on the news days are -0.2% over all benchmark returns, which confirms that our sample mostly captures disclosures of tweeted firms' adverse news. CARs over [0, +1] are barely changed from CARs on the initial news days, inconsistent with a drift. Table 6, Panel B reports returns to tweeted firms surrounding NPD days, which are largely insignificant. This result is less consistent with the dissemination hypothesis than the disclosure hypothesis because the former would predict a second negative market reaction to tweeted firms surrounding NPDs.[13]

[13] The prediction for this event return is unclear under the disclosure hypothesis. Any new information released by the tweeting firm via an NPD can also affect the tweeted firm through rivalry and technology spillovers, and the net effect depends on which spillover dominates. Evidence from univariate analyses also does not indicate dissemination. We find that 41% of NPDs in our sample have no retweets and 82% of NPDs have five retweets or fewer; 52% of NPDs have no likes and 75% of NPDs have five likes or fewer; and 86% of NPDs have no replies and 98% of

Table 5
Characteristic-adjusted event returns to tweeting firms: Univariate sorts.

Panel A: Book-to-market-adjusted CARs to tweeting firms surrounding NPDs

	Including same-day NPDs		Excluding same-day NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.008***	0.008***	0.009***	0.008***
[0, +1]	0.016***	0.015***	0.017***	0.015***
[−2, −1]	−0.002	−0.003*	−0.002	−0.003*
No. of obs.	558	558	386	386

Panel B: Profitability-adjusted CARs to tweeting firms surrounding NPDs

	Including same-day NPDs		Excluding same-day NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.009***	0.009***	0.010***	0.009***
[0, +1]	0.017***	0.016***	0.018***	0.017***
[−2, −1]	−0.000	−0.002	−0.001	−0.003
No. of obs.	558	558	386	386

Panel C: Investment-adjusted CARs to tweeting firms surrounding NPDs

	Including same-day NPDs		Excluding same-day NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.009***	0.009***	0.009***	0.009***
[0, +1]	0.016***	0.015***	0.018***	0.017***
[−2, −1]	−0.002	−0.003*	−0.002	−0.003
No. of obs.	563	563	389	389

Panel D: Book-to-market-adjusted CARs to tweeting firms surrounding initial news days

	Including same-day NPDs		Excluding same-day NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.003***	0.003**	−0.001	−0.001
[0, +1]	0.007***	0.006***	0.001	0.001
[−2, −1]	0.000	−0.001	0.000	−0.002
No. of obs.	384	384	212	212

Panel E: Profitability-adjusted CARs to tweeting firms surrounding initial news days

	Including same-day NPDs		Excluding same-day NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.003***	0.003***	−0.001	−0.001
[0, +1]	0.009***	0.008***	0.003	0.001
[−2, −1]	0.002	0.000	0.001	−0.001
No. of obs.	384	384	212	212

Panel F: Investment-adjusted CARs to tweeting firms surrounding initial news days

	Including same-day NPDs		Excluding same-day NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.003**	0.003**	−0.001	−0.002
[0, +1]	0.007***	0.006***	−0.000	0.001
[−2, −1]	−0.000	−0.001	−0.000	−0.001
No. of obs.	388	388	214	214

Panels A-C report the mean book-to-market-adjusted, profitability-adjusted, and investment-adjusted CARs to tweeting firms surrounding NPDs, respectively. Panels D-E report the corresponding CARs to tweeting firms surrounding initial news days, respectively. The first two columns of each panel report CARs including same-day NPDs, and the last two columns of each panel report CARs excluding same-day NPDs. Each column tests whether the characteristic-adjusted CAR is significantly different from zero. Detailed variable definitions are in Appendix A. Samples include individual NPD and initial news events for which characteristic-adjusted CARs are available for tweeting firms as indicated in each panel. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

We again check the robustness of these results using characteristic-adjusted CARs to ensure that the observed event returns to tweeted firms are not explained by other news of their fundamentals. Table 7 repeats the analyses in Table 6 using excess returns over benchmark returns on the univariate-sorted portfolios (i.e., CARs adjusted by BM, profitability, and investment). Samples cover individual NPDs and initial news events for which characteristic-adjusted CARs can be computed for tweeted firms. We continue to find that tweeted firms experience small negative returns when the initial news came out, but their returns are either small or insignificant surrounding NPDs. Table OA3 of the Online Appendix presents similar results using excess returns over benchmark returns on the bivariate-sorted portfolios (i.e., CARs adjusted by BM and

NPDs have five replies or fewer. Twitter does not provide historical information about the number of followers.

Table 6
Market- and industry-adjusted event returns to tweeted firms.

Panel A: Market- and industry-adjusted CARs to tweeted firms surrounding initial news days

	CARs over the market portfolio		CARs over the industry portfolio	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	−0.002**	−0.002**	−0.002**	−0.002***
[0, +1]	−0.002**	−0.002**	−0.002	−0.003***
[−2, −1]	0.002**	0.001	0.001	0.001
No. of obs.	388	388	388	388

Panel B: Market- and industry-adjusted CARs to tweeted firms surrounding NPDs

	CARs over the market portfolio		CARs over the industry portfolio	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.001	0.000	0.001*	0.001
[0, +1]	0.001	0.000	0.002	0.001
[−2, −1]	0.000	0.000	0.001	0.000
No. of obs.	563	563	563	563

Panel A reports the mean market- or industry-adjusted CARs to tweeted firms surrounding initial news days. Panel B reports the corresponding CARs to tweeted firms surrounding NPDs. The first two columns of each panel report market-adjusted CARs, and the last two columns of each panel report industry-adjusted CARs. Each column tests whether the market- or industry-adjusted CAR is significantly different from zero. Detailed variable definitions are in Appendix A. Samples include individual NPD, and initial news events for which market- and industry-adjusted CARs are available for tweeted firms as indicated in each panel. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

Table 7
Characteristic-adjusted event returns to tweeted firms: Univariate sorts.

Panel A: Book-to-market-adjusted CARs to tweeted firms

	Surrounding initial news days		Surrounding NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	−0.002**	−0.002**	0.001*	0.001
[0, +1]	−0.002*	−0.003**	0.002*	0.001
[−2, −1]	0.002	0.001	0.001	0.000
No. of obs.	360	360	521	521

Panel B: Profitability-adjusted CARs to tweeted firms

	Surrounding initial news days		Surrounding NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	−0.002**	−0.002**	0.002**	0.001
[0, +1]	−0.002*	−0.003**	0.002**	0.001
[−2, −1]	0.002	0.001	0.001	0.000
No. of obs.	360	360	521	521

Panel C: Investment-adjusted CARs to tweeted firms

	Surrounding initial news days		Surrounding NPDs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	−0.002**	−0.002**	0.001*	0.001
[0, +1]	−0.002*	−0.003***	0.002*	0.001
[−2, −1]	0.002*	0.001	0.001	0.000
No. of obs.	364	364	527	527

Panels A-C report the mean book-to-market-adjusted, profitability-adjusted, and investment-adjusted CARs to tweeted firms. The first two columns of each panel report CARs surrounding initial news days, and the last two columns of each panel report CARs surrounding NPDs. Each column tests whether the characteristic-adjusted CAR is significantly different from zero. Detailed variable definitions are in Appendix A. Samples include individual NPD, and initial news events for which characteristic-adjusted CARs are available for tweeted firms as indicated in each panel. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

profitability, BM and investment, and profitability and investment).

To give a better sense of economic magnitude, we provide a back-of-the-envelope calculation of the dollar impact on tweeting and tweeted firms surrounding event days in Table 8, which corresponds to excess returns reported in Tables 4 and 6 that are directional and statistically significant; samples are also based on these two tables. Panel A of Table 8 reports the average dollar gains for tweeting firms on the day of NPD and over the two-day window. Panel B reports the corresponding value changes for tweeting firms excluding NPDs retweeted on initial

Table 8
Changes in market capitalization surrounding NPDs and initial news days.

Panel A: Dollar impact on tweeting firms surrounding NPDs (in millions)

	Based on market-adjusted CARs		Based on industry-adjusted CARs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	26.316	24.078	26.105	18.949
[0, +1]	51.763	46.495	50.801	36.632
No. of obs.	599	599	599	599

Panel B: Dollar impact on tweeting firms surrounding NPDs excluding same-day NPDs (in millions)

	Based on market-adjusted CARs		Based on industry-adjusted CARs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	34.305	32.597	29.677	20.031
[0, +1]	53.159	47.481	48.172	34.925
No. of obs.	411	411	411	411

Panel C: Dollar impact on tweeting firms surrounding initial news days (in millions)

	Based on market-adjusted CARs		Based on industry-adjusted CARs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	9.855	9.731	13.915	11.032
[0, +1]	26.120	24.437	30.862	26.407
No. of obs.	411	411	411	411

Panel D: Dollar impact on tweeted firms surrounding initial news days (in millions)

	Based on market-adjusted CARs		Based on industry-adjusted CARs	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	−131.008	−154.377	−85.473	−219.746
[0, +1]	−162.898	−259.546	−78.137	−320.962
No. of obs.	388	388	388	388

Panel A reports the average change in market capitalization for tweeting firms surrounding NPDs. Panel B reports the corresponding change for tweeting firms surrounding NPDs excluding same-day NPDs. Panel C reports the corresponding change for tweeting firms surrounding initial news days. Panel D reports the corresponding change for tweeted firms surrounding initial news days. Change for each firm is calculated by multiplying the firm's CAR over the event window by the firm's market capitalization on the trading day prior to the event day, in millions. The first two columns of each panel are based on CARs relative to market portfolios, and the last two columns of each panel are based on CARs relative to industry portfolios. Samples include individual NPD, and initial news events for which market- and industry-adjusted CARs are available for tweeting or tweeted firms as indicated in each panel.

news days. Value change for each firm is calculated by multiplying the firm's market- or industry-adjusted CAR over an event window by the firm's market capitalization on the trading day before the NPD day. Panel C reports the average dollar gains for tweeting firms on the initial news day and over the two-day window. Panel D reports the average dollar losses for tweeted firms on the initial news day and over the two-day window. Numbers in Panels C-D are analogous to those in Panels A-B but are based on the market capitalization on the trading day before the initial news day.

There are two insights from Table 8. First, although the excess returns reported in Table 4 may appear modest, the dollar gains for tweeting firms are sizable surrounding NPD days (with an average two-day gain of $34.9–$53.2 million) and are larger than their dollar gains surrounding initial news days (with an average two-day gain of $24.4–$30.9 million). Second, the magnitude of the dollar gains for tweeting firms surrounding NPD days is a fraction of the magnitude of the dollar losses for tweeted firms surrounding initial news days (with an average two-day loss of $78.1–$321 million) because tweeted firms are, on average, larger than tweeting firms.

In untabulated analyses, we similarly calculate the dollar impact on tweeting and tweeted firms surrounding event days based on characteristic-adjusted CARs. Surrounding NPD days, the tweeting firms enjoy an average two-day gain of $34.7–$57.8 million using excess returns over the univariate-sorted portfolios (corresponding to Table 5) and $34.3–$57.1 million using excess returns over the bivariate-sorted portfolios (corresponding to Table OA2). Surrounding initial news days, the tweeted firms suffer an average two-day loss of $93.8–$172 million using excess returns over the univariate-sorted portfolios (corresponding to Table 7) and of $117.1–$194.9 million using excess returns over the bivariate-sorted portfolios (corresponding to Table OA3).

4.2 NPD and spillover strength

The patterns of event returns provide initial support for the disclosure hypothesis. Recall that this hypothesis builds on the framework of BSV and posits that corporate NPDs are motivated by spillover effects. We conduct two analyses in this section to shed light on these spillover effects and the benefits of issuing NPDs.

The first analysis speaks to product market rivalry spillover. We calculate two measures to capture rivalry intensity. The first measure, *Prod proximity*, follows BSV. BSV build it by first constructing an N-vector for each firm-year, with each element of the vector representing the firm's share of sales in a four-digit SIC industry and N being the total number of industries in the year. They then compute, for a pair of firm i-j, the uncentered correlation between two firms' vectors. The second measure, *Prod similarity*, uses firms' product descriptions as opposed to share of sales per industry as the basis to measure product market rivalry. HP create this measure in four steps. First, they gather firms' 10-K filings in a year and extract product descriptions from these filings. Second, they build a dictionary of words pertinent to product descriptions for the year. Third, based on the dictionary, they construct a binary *N*-vector for each firm summarizing its word usage in product description. Finally, for a pair of firm *i-j, Prod similarity* is the dot product of two firms' normalized vectors. By construction, both measures are positively correlated with the intensity of product market rivalry spillover.

We link the two measures to NPD propensity by estimating the following probit regression:

$$NPD_{i-j,t} = \alpha + \beta_1 Product\ market\ rivalr\ y_{i-j,t} + \beta_2 Control_{i-j,t} + \beta_3 Firm_i + \beta_4 Year_t + \varepsilon_{i-j,t}, \quad (1)$$

where subscript *i* indexes the focal firm (i.e., the firm that decides whether to issue NPDs), *j* indexes the peer firm based on the TNIC-3 classification, *i-j* indexes the pair, and *t* indexes fiscal year. *NPD* measures the probability of issuing NPDs, which equals one if firm *i* posts at least one tweet through its corporate Twitter account disclosing adverse news of firm *j* in year *t* and equals zero otherwise. *Product market rivalry* represents either *Prod proximity* or *Prod similarity. Control* is a vector of controls defined for each firm pair-year, including the ratio of firm *i*'s market capitalization to firm *j*'s (*Relative size*), and the differences between firm *i*'s and *j*'s market-to-book (*Relative MB*), return-on-assets (*Relative ROA*), and debt-to-assets (*Relative lev*) in year *t*. We further include focal firm fixed effects to control for time-invariant financial characteristics that may explain firms' tendency to issue NPDs and year fixed effects to control for intertemporal variation. We cluster standard errors by focal firm and year and adjust for heteroskedasticity.

We estimate Eq. (1) using two samples. Reflecting our focus on peer disclosure, we construct both samples at the firm pair-year level. The first sample, labeled "unconditional sample," includes 58,195 firm pair-year observations with data available to calculate the main variables. Analyses using this sample allow focal firm *i* to decide whether to issue NPDs about peer firm *j* with no requirements of adverse news occurring to firm *j* in year *t*. This is possible considering that a focal firm may actively gather and spread adverse news of its peers. The second sample, labeled "conditional sample," includes 3614 firm pair-year observations for which the peer firm receives at least one NPD in year *t*. By design, this sample ensures that there is adverse news occurring to firm *j* in year *t* and the news is deemed tweetable by at least one peer firm. When running analyses with the conditional sample, we further include peer firm fixed effects to control for time-invariant characteristics that may explain a firm's tendency to be tweeted about.[14] Table 9, Panels A-B report descriptive statistics separately for the unconditional sample and the conditional sample. As shown, the unconditional probability of issuing NPDs in a year is 0.5%, while the conditional probability is much higher at 7.3%.

Table 10, Panel A presents the results of estimating Eq. (1) using the unconditional sample. Column (1) shows that *Prod proximity*, our first measure of rivalry spillover, has a positive coefficient estimate, significant at the 1% level. Based on the marginal effect, a one standard deviation increase in *Prod proximity* is associated with an increase of 0.12% in the probability of issuing NPDs, 24% of the unconditional probability 0.5%. Column (2) replaces *Prod proximity* with *Prod similarity.* The coefficient estimate is also positive and significant at the 1% level. A one standard deviation increase in *Prod similarity* is associated with an increase of 0.18% in the probability of issuing NPDs, 36% of the unconditional probability. Table 10, Panel B repeats the analyses using the conditional sample. Both measures of rivalry spillover remain positively related to NPD propensity. The marginal effects are larger in absolute magnitude but are comparable in relative magnitude: a one standard deviation increase in *Prod proximity* (*Prod similarity*) is associated with an increase of 1.7% (2.5%) in the probability of issuing NPDs, 23% (34%) of the conditional probability 7.3%.

The positive relation between rivalry intensity and NPD propensity further supports the disclosure hypothesis, which predicts that a firm has greater incentives to issue NPDs about close rivals because disclosure benefits are higher. This result can also be consistent with the dissemination hypothesis, which predicts that a firm has greater incentives to diffuse information from close rivals' adverse news via an NPD because this spillover positively affects the firm.

Turning to the controls, they are mostly insignificant in Table 10, except for *Relative size*, the ratio of firm *i*'s market capitalization to firm *j*'s, in Panel A. This result suggests that, unconditionally, a firm is more likely to tweet a peer firm's adverse news if it is relatively small.

The second analysis speaks to technology spillover. BSV build a measure of technology proximity analogous to *Prod proximity*. They first define an *N*-vector for each firm-year, with each element of the vector representing the firm's share of patents in a technology class and *N* being the total number of technology classes assigned by the United States Patent and Trademark Office in the year. They then compute, for a pair of firm *i-j*, the uncentered correlation between two firms' vectors. We follow this approach to compute the measure from 2009 to 2014, for which we have patent data. For each year, we accumulate the patents applied by a firm over the past 20 years (the typical term of a US patent from the filing date) to calculate its share in a technology class. We label the resulting measure *Tech proximity*, and it increases with the intensity of technology spillover.

We similarly link *Tech proximity* to NPD propensity by estimating a probit regression:

$$NPD_{i-j,t} = \alpha + \beta_1 Tech\ proximit\ y_{i-j,t} + \beta_2 Control_{i-j,t}$$

[14] We include only focal firm fixed effects when estimating Eq. (1) with the unconditional sample because including peer firm fixed effects would drop a firm pair if the peer firm has never been tweeted about during the sample period, significantly shrinking the size of the unconditional sample and making it very close to the conditional sample.

Table 9
Descriptive statistics of main variables.

Panel A: Unconditional sample						
Variable	N	Mean	SD	25%	Median	75%
Dependent variable						
NPD	58,195	0.005	0.068	0.000	0.000	0.000
Product market rivalry and information uncertainty						
Prod proximity	58,195	0.202	0.392	0.000	0.000	0.000
Prod similarity	58,195	0.108	0.042	0.086	0.112	0.133
Tech proximity	26,691	0.197	0.326	0.000	0.000	0.341
Control variables						
Relative size	58,195	1.172	0.624	0.779	1.024	1.375
Relative MB	58,195	0.398	10.157	−1.803	0.306	2.433
Relative ROA	58,195	0.013	0.212	−0.080	0.005	0.087
Relative lev	58,195	−0.003	0.228	−0.129	0.000	0.125
Panel B: Conditional sample						
Variable	N	Mean	SD	25%	Median	75%
Dependent variable						
NPD	3614	0.073	0.260	0.000	0.000	0.000
Product market rivalry and information uncertainty						
Prod proximity	3614	0.240	0.413	0.000	0.000	0.298
Prod similarity	3614	0.116	0.042	0.096	0.119	0.141
Tech proximity	1815	0.284	0.345	0.000	0.000	0.561
Control variables						
Relative size	3614	0.721	0.285	0.537	0.682	0.838
Relative MB	3614	0.428	9.510	−3.013	−0.580	1.793
Relative ROA	3614	−0.079	0.170	−0.152	−0.059	0.005
Relative lev	3614	−0.039	0.204	−0.174	−0.074	0.055

Panel A reports the number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile for the main variables used in the regression analyses. This panel uses mainly the unconditional sample of 58,195 firm pair-years between fiscal year 2009 and 2017. The focal firm of each pair is labeled *i* and the other firm *j*. Panel B reports the corresponding summary statistics using mainly the conditional sample of 3614 firm pair-years for which firm *j* receives at least one NPD during the year. Sample size for *Tech proximity* in both panels is limited by the availability of patent data. *NPD* is an indicator variable that denotes whether firm *i* issued NPD about firm *j* in a year. *Prod similarity* is the pairwise product cosine similarity measure of HP. *Prod proximity* and *Tech proximity* are the pairwise product proximity measure and technology proximity measure of BSV. Controls include the ratio of firm *i*'s market value of equity to firm *j*'s (*Relative size*); the difference between two firms' market-to-book (*Relative MB*); the difference between two firms' return-on-assets (*Relative ROA*); and the difference between two firms' debt-to-assets (*Relative lev*). Detailed variable definitions are in Appendix A.

$$+ \beta_3 Firm_i + \beta_4 Year_t + \varepsilon_{i-j,t}. \tag{2}$$

Table 9, Panels A-B report the descriptive statistics for *Tech proximity*. Subscripts and other variables are defined above. We again use two samples. The unconditional sample includes 26,691 firm pair-year observations, and the conditional sample includes 1815 firm pair-year observations, both from 2009 to 2014. The decrease in sample size relative to the samples used in Table 10 is due to patent data availability.[15] We similarly include focal firm and year fixed effects and cluster standard errors at the same levels. We further include peer firm fixed effects when using the conditional sample.

Table 11 presents the results of estimating Eq. (2). We see a significantly positive coefficient estimate on *Tech proximity*, using either sample. In terms of economic significance, a one standard deviation increase in *Tech proximity* is associated with an increase of 0.23% in the unconditional probability of issuing NPDs and an increase of 4.1% in the conditional probability of issuing NPDs, 46% and 56% of the sample average, respectively.

These results are consistent with the disclosure hypothesis, which predicts that a firm has greater incentives to issue NPDs about peers with which they have closer technology proximity because disclosure benefits are higher. It is inconsistent with the dissemination hypothesis, which predicts that a firm has fewer incentives to diffuse information from peer firms' adverse news via an NPD when technology spillover is stronger because this spillover supposedly negatively affects the firm.

In Table OA4 of the Online Appendix, we examine whether the market reaction to NPDs varies with the strength of spillovers. We conduct three sets of cross-sectional analyses, splitting the sample based on the level of *Prod proximity, Prod similarity*, and *Tech proximity*, respectively. We report only the one- and two-day CARs over the value-weighted portfolios post-NPDs for brevity. As Panel A shows, tweeting firms, on average, enjoy a more positive market reaction surrounding NPDs when the spillover links are stronger (i.e., when *Prod proximity, Prod similarity*, and *Tech proximity* are above their respective sample median value). The CAR over [0, +1] is significantly more positive for firm pairs with stronger rivalry spillover than for firm pairs with weaker rivalry spillover (1.8% versus 1.2%−1.3% based on *Prod proximity* and 1.9% versus 1.4% based on *Prod similarity*) and is also more positive for firm pairs with stronger technology spillover than for firm pairs

[15] Patent data in most publicly available databases are not up to date. The NBER Patent Data Project provides US patent data for 1976–2006, and Harvard Business School Patent Network Dataverse provides patent data for 1975–2010. We obtained the patent data used here from Xuan Tian, which are manually collected but are still available only through 2014.

Table 10
NPD and product market rivalry spillover.

Dependent Variable	(1) Panel A: Unconditional sample NPD_t	(2)	(3) Panel B: Conditional sample NPD_t	(4)
Prod proximity	0.290***		0.322***	
	(0.058)		(0.083)	
	[0.003]		[0.040]	
Prod similarity		3.901***		5.455***
		(0.672)		(1.274)
		[0.042]		[0.595]
Relative size	−3.462***	−3.490***	0.305	0.152
	(0.344)	(0.360)	(0.829)	(0.868)
Relative MB	0.005	0.006*	0.006	0.008
	(0.003)	(0.003)	(0.005)	(0.005)
Relative ROA	0.102	0.005	0.305	0.130
	(0.371)	(0.393)	(0.472)	(0.490)
Relative lev	−0.011	−0.009	−0.361	−0.247
	(0.189)	(0.193)	(0.475)	(0.481)
Intercept	0.869***	0.547*	−1.226	−1.451*
	(0.243)	(0.302)	(0.788)	(0.875)
Focal firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Peer firm fixed effects	No	No	Yes	Yes
No. of obs.	58,195	58,195	3614	3614
Pseudo R^2	0.267	0.271	0.215	0.223

This table reports the probit regression results on the relation between the propensity to issue NPDs and product market rivalry spillover. Columns (1)-(2) use the unconditional sample that comprises 58,195 firm pair-years between fiscal year 2009 and 2017, and columns (3)-(4) use the conditional sample that comprises 3614 firm pair-years between fiscal year 2009 and 2017, for which firm *j* receives at least one NPD during the year. The focal firm of each pair is labeled *i* and the other firm *j*. *NPD* denotes the issuance of NPDs. Product market rivalry spillover is measured using *Prod proximity* in columns (1) and (3) and *Prod similarity* in columns (2) and (4), respectively. Controls include *Relative size, Relative MB, Relative ROA, Relative lev* as well as fixed effects as indicated in each column. Detailed variable definitions are in Appendix A. Standard errors, displayed in parentheses below coefficient estimates, are adjusted for heteroskedasticity and are clustered by focal firm and year. For *Prod proximity* and *Prod similarity*, the marginal effects (df/dx) are displayed below the standard errors. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

with weaker technology spillover (1.7%−1.8% versus 0.5% based on *Tech proximity*). Results are similar using CARs over the equal-weighted portfolios. Results excluding NPDs retweeted on initial news days are similar and reported in Table OA4, Panel B, with the exception that the difference in CARs between subsamples is not statistically significant when splitting the sample based on *Prod similarity*.[16]

4.3 NPD and spillover clarity

The previous section shows that NPD propensity and the market reaction to NPDs increase with the strength of spillover links. In this section, we examine whether NPD propensity and the market reaction to NPDs also vary with the clarity of spillover links.

We define two variables to capture the clarity of two firms' peer relationship. *SIC3Brdth* measures the breadth of a three-digit SIC industry. Specifically, we compute, for each firm-year, the ratio of the number of firms in its three-digit SIC industry to the number of firms in its TNIC-3 industry and then take the arithmetic mean of the two ratios for each pair of firm *i-j* in year *t*. *DiffSIC3* is an indicator that equals one if a pair of peer firms formed using the TNIC-3 classification fall into different three-digit SIC industries in year *t* and equals zero if the two firms share the same three-digit SIC code.

We first link these two variables to NPD propensity by estimating the following probit regression:

$$NPD_{i-j,t} = \alpha + \beta_1 SIC3Brdth(DiffSIC3)_{i-j,t} + \beta_2 Control2_{i-j,t} + \beta_3 Industry_k + \beta_4 Year_t + \varepsilon_{i-j,t}. \quad (3)$$

SIC3Brdth and *DiffSIC3*, defined above, are negatively related to the clarity of peer relationships. *Control2* includes basic controls defined in Section 4.2 (*Relative size, Relative MB, Relative ROA*, and *Relative lev*) and three measures of spillover strength (*Prod proximity, Prod similarity*, and *Tech proximity*). We focus on the conditional sample and include year and industry fixed effects because *SIC3Brdth* and *DiffSIC3* are defined at the industry level rather than the firm level. The sample further shrinks relative to the conditional sample used in Table 11 because some firms do not have three-digit SIC designations in a year. Table 12 reports the regression results. Both *SIC3Brdth* and *DiffSIC3* are posi-

[16] For brevity, we report only the one- and two-day CARs post-NPDs. In untabulated analyses, we find that similar to the results reported in Table 4, CARs to tweeting firms prior to NPDs are largely insignificant in all subsamples.

Table 11
NPD and technology spillover.

	(1) Unconditional sample	(2) Conditional sample
Dependent variable	NPD_t	
Tech proximity	0.492***	0.970***
	(0.098)	(0.266)
	[0.007]	[0.118]
Relative size	−3.662***	0.657
	(0.579)	(0.886)
Relative MB	0.005	0.004
	(0.006)	(0.006)
Relative ROA	0.638**	0.455
	(0.259)	(0.897)
Relative lev	0.105	−1.451***
	(0.211)	(0.559)
Intercept	0.529	−2.459***
	(0.475)	(0.936)
Focal firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Peer firm fixed effects	No	Yes
No. of obs.	26,691	1815
Pseudo R^2	0.273	0.217

This table reports the probit regression results on the relation between the propensity to issue NPDs and technology spillover. Column (1) uses the unconditional sample that comprises 26,691 firm pair-years between fiscal year 2009 and 2014, and column (2) uses the conditional sample that comprises 1815 firm pair-years between fiscal year 2009 and 2014, for which firm *j* receives at least one NPD during the year. The sample size is limited by data availability of *Tech proximity*. The focal firm of each pair is labeled *i* and the other firm *j*. *NPD* denotes the issuance of NPDs. Technology spillover is measured using *Tech proximity* in both columns. Controls include *Relative size, Relative MB, Relative ROA, Relative lev* as well as fixed effects as indicated in each column. Detailed variable definitions are in Appendix A. Standard errors, displayed in parentheses below coefficient estimates, are adjusted for heteroskedasticity and are clustered by focal firm and year. For *Tech proximity*, the marginal effects (df/dx) are displayed below the standard errors. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

tively related to NPD propensity. That is, a firm is more likely to issue NPDs when its peer relationship with the firm having adverse news is less clear to the market.

In Table OA5 of the Online Appendix, we further examine whether the market reaction to NPDs varies with the clarity of spillover links. As in Table OA4 of the Online Appendix, we conduct two sets of cross-sectional analyses, splitting the sample based on the level of *SIC3Brdth* and *DiffSIC3*, respectively. We again report only the one- and two-day CARs over the value-weighted portfolios post-NPDs for brevity. As Panel A shows, tweeting firms, on average, enjoy a more positive market reaction surrounding NPDs when the spillover links are less clear to the market (i.e., when *SIC3Brdth* is above sample median or *DiffSIC3*=1). The two-day CAR is significantly more positive for firm pairs in a broader three-digit SIC industry than for firm pairs in a narrower three-digit SIC industry (2.1% versus 1%−1.1%), and the one-day CAR is more positive for firm pairs with different three-digit SIC codes than for firm pairs with the same three-digit SIC code (1.1% versus 0.7%). Results in Panel B are similar when we exclude NPDs retweeted on initial news days.

These results can be consistent with the disclosure hypothesis if the firm seeks to provide more information about the peer relationship (or its own products), and this information is more valuable when the peer relationship is less clear to the market. These results may also be consistent with the dissemination hypothesis if the firm seeks to attract attention and investors respond to attention.

4.4 NPD and firm quality

We next turn to the disclosure costs of NPDs. As discussed earlier, corporate NPDs are unlikely cheap talk because such disclosures may expose firms to close scrutiny and monetary and reputation loss if they turn out to be not credible. Although these potential risks and costs are difficult to quantify, one would expect them to be lower for firms of higher quality because these firms can better withstand scrutiny. Thus, we check whether firms that do issue NPDs are more likely of high quality.

For each of the 228 unique tweeting firm-years shown in Table 3, Panel B (labeled the treatment group), we identify a control firm in the same TNIC-3 industry as the treatment firm with similar preevent characteristics and corporate Twitter account that did not issue an NPD in the year (labeled the control group). We include five basic characteristics *Size, MB, Lev, ROA*, and cash flow-on-

Table 12
NPD and spillover clarity.

Dependent variable	(1)	(2)
	NPD_t	
SIC3Brdth	0.126***	
	(0.046)	
	[0.017]	
DiffSIC3		0.275*
		(0.161)
		[0.036]
Prod proximity	0.262*	0.421**
	(0.155)	(0.184)
Prod similarity	3.835**	3.204*
	(1.837)	(1.804)
Tech proximity	0.407	0.163
	(0.265)	(0.229)
Intercept	−1.222***	−0.831*
	(0.517)	(0.458)
Basic controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
No. of obs.	1512	1512
Pseudo R^2	0.179	0.169

This table reports the probit regression results on the relation between the propensity to issue NPDs and spillover clarity. Both columns use the conditional sample that comprises 1512 firm pair-years between fiscal year 2009 and 2014, for which firm *j* receives at least one NPD during the year. The sample size is limited by data availability of *Tech proximity, SIC3Brdth*, and *DiffSIC3*. The focal firm of each pair is labeled *i* and the other firm *j*. *NPD* denotes the issuance of NPDs. Spillover clarity is measured using *SIC3Brdth* in column (1) and *DiffSIC3* in column (2). Controls include basic controls (*Relative size, Relative MB, Relative ROA, Relative lev*), *Prod proximity, Prod similarity, Tech proximity* as well as fixed effects as indicated in each column. Detailed variable definitions are in Appendix A. Standard errors, displayed in parentheses below coefficient estimates, are adjusted for heteroskedasticity and are clustered by focal firm and year. For *SIC3Brdth* and *DiffSIC3*, the marginal effects (df/dx) are displayed below the standard errors. *** (**) (*) indicates significance at the 1% (5%) (10%) level using the two-tailed tests.

assets (*CFOA*) and year fixed effects in the propensity score matching algorithm.[17] Starting from 228 unique tweeting firm-years, we end up with 210 unique pairs of treatment-control firms with close propensity scores and financials available in both fiscal year *t*-1 and year $t+1$, with *t* indicating the year to which the NPD belongs to. We do not construct the sample at the individual NPD level (as in Table 3, Panel A) or the firm pair-year level (as in Table 3, Panel C) because including a tweeting firm-year multiple times in the analysis would artificially boost test power and lead to underestimated standard errors.

Table 13, Panel A shows that differences in propensity scores between the treatment and control firms are miniscule. Panel B shows no significant differences in the pre-NPD firm characteristics that are used to match. Panel C conducts a difference-in-differences (DiD) test to compare the two groups of firms' change in product market outcomes and operating performance from year *t*-1 to year $t+1$. We study three product market outcomes, including $\Delta AdjSale$ (annual growth in industry-adjusted sales), $\Delta MktShr$ (annual growth in market share), and $\Delta Cntrct$ (annual growth in the number of sales contracts reported in the FactSet database). FactSet collects data on sales contracts associated with major customers (sales to whom account for 10% or more of the firm's total sales) and large sales contracts associated with nonmajor customers voluntarily disclosed by the firm. We also study two measures of operating performance, including *ROA* (return-on-assets) and *CFOA* (cash flow-to-assets). Results show that the increase in $\Delta AdjSale$, $\Delta MktShr$, and $\Delta Cntrct$ from the year before NPD to the year after is 25.7, 1.9, and 74.3% higher for treatment firms than for control firms, respectively, and the increase in *ROA* and *CFOA* is also 3.6 and 2.3% higher for treatment firms, respectively; the differences are statistically significant using the one-tailed *t*-test.

Panel D undertakes a multivariate DiD test to compare the two groups of firms' change in product market outcomes and operating performance. We estimate the following model:

$$Performance_{i,t} = \alpha + \beta_1 NPD_i \times POST_{i,t} + \beta_2 POST_{i,t} + \beta_3 Control3_{i,t} + \beta_4 Firm_i + \beta_5 Year_t + \varepsilon_{i,t}, \quad (4)$$

where *Performance* is one of the three product market measures ($\Delta AdjSale$, $\Delta MktShr$, and $\Delta Cntrct$) or the two operating performance measures (*ROA* and *CFOA*). *NPD* denotes firms, equaling one for treatment firms and zero for control firms; *POST* denotes periods, equaling one for post-treatment periods and zero for pretreatment periods; and $NPD \times POST$ is the DiD estimator, the variable of interest. Controls include *Size, MB, ROA*, and *LEV* but exclude *ROA* in the regressions, with *ROA* and *CFOA* as the dependent variable. We include two more years in this analysis (i.e., year *t*-2 and $t+2$) to allow for the inclusion of firm and year fixed effects.[18] As Panel D shows, the coefficient estimate on $NPD \times POST$ is positive and significant at the 10% level or lower in all five regressions using one-tailed t-tests and is positive and significant at the 10% level or lower in three out of the five regressions using two-tailed t-tests. These results show that the univariate DiD results are not sensitive to controlling for firm characteristics and fixed effects and provide further evidence that NPD tweeting firms outperform non-NPD-tweeting peer firms.

Panel E studies event returns to control firms as a falsification test; samples include NPD events for which market- and industry-adjusted CARs can be computed for matched control firms. Results show that on the NPD days of treatment firms and the days immediately after, the matched control firms do not experience positive returns. The fact that NPD issuing firms outperform their non-NPD issuing peers points to the existence of disclosure costs, which in turn suggests that corporate NPDs are not cheap talk. It also corroborates the earlier finding of a positive market reaction to tweeting firms surrounding NPDs.

[17] When studying product market outcomes, we further include the preevent level of each outcome as a matching variable to ensure that the parallel trend is met. Including these outcomes sequentially helps preserve sample size. Table 13, Panels A-B report propensity scores and preevent financials for the sample matched using five basic characteristics.

[18] The number of observations in Panel D is slightly below eight times of the number of observations in Panel C (1,564 versus 1,680) because the analysis requires availability of firm financials in year *t-2* and $t+2$ in addition to *t*-1 and $t+1$.

Table 13

Performance of NPD tweeting firms versus non-NPD-tweeting firms.

Panel A: Estimated propensity score distribution

Propensity scores	No. of obs.	SD	Min	P25	Median	Mean	P75	Max
Tweeting firms	210	0.014	0.882	0.976	0.983	0.980	0.988	0.999
Control firms	210	0.013	0.898	0.976	0.983	0.980	0.988	0.997
Difference	210	0.001	-0.016	0.000	0.000	0.000	0.000	0.002

Panel B: Differences in preevent basic characteristics

	Tweeting firms	Control firms	Differences	*p*-value
Size	6.919	6.769	−0.150	0.486
MB	4.557	4.160	−0.397	0.490
ROA	−0.032	−0.026	0.006	0.400
Lev	0.122	0.115	−0.007	0.694
CFOA	0.074	0.090	0.016	0.220

Panel C: Univariate DiD test of product market outcomes and operating performance

	N	Tweeting firms	Control firms	DiD estimator	*p*-value
$\Delta\text{AdjSale}_{t+1} - \Delta\text{AdjSale}_{t\text{-}1}$	210	0.309	0.052	0.257	0.035
$\Delta\text{MktShr}_{t+1} - \Delta\text{MktShr}_{t\text{-}1}$	210	0.020	0.002	0.019	0.091
$\Delta\text{Cntrct}_{t+1} - \Delta\text{Cntrct}_{t\text{-}1}$	210	−0.057	−0.800	0.743	0.058
$\text{ROA}_{t+1} - \text{ROA}_{t\text{-}1}$	210	0.005	−0.031	0.036	0.014
$CFOA_{t+1}$ - $CFOA_{t\text{-}1}$	210	0.006	−0.017	0.023	0.018

Panel D: Multivariate DiD test of product market outcomes and operating performance

Dependent variable	(1) $\Delta AdjSale_t$	(2) $\Delta MktShr_t$	(3) $\Delta Cntrct_t$	(4) ROA_t	(5) $CFOA_t$
NPD × *POST*	0.152*	0.008**	0.214*	0.043***	0.026***
	(0.110)	(0.005)	(0.154)	(0.017)	(0.011)
POST	−0.006	−0.005	−0.819*	−0.041***	−0.015
	(0.093)	(0.004)	(0.460)	(0.015)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
No. of obs.	1564	1564	1564	1564	1564
R^2	0.271	0.176	0.412	0.671	0.723

Panel E: Market- and industry-adjusted CARs to matched non-NPD-tweeting firms surrounding NPDs of tweeting firms

	CARs over the market portfolio		CARs over the industry portfolio	
Event window	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
[0, 0]	0.000	0.000	0.000	−0.000
[0, +1]	0.000	−0.000	0.001	−0.000
No. of obs.	570	570	570	570

This table examines the performance of tweeting firms in the years surrounding NPDs compared to a sample of matched control firms. Starting with the 228 unique tweeting firm-years in the sample, we match each of the tweeting firms with a non-NPD-tweeting peer firm in the year of NPD (year *t*) using propensity score matching without replacement, and we require both tweeting and control firms to have data available to calculate firm financials in year *t*-1 and *t* + 1. The basic matching variables include *Size*, *MB*, *Lev*, *ROA*, and *CFOA* in year *t*-1. When studying the product market outcomes, we further include each of them as a matching variable. Panel A reports the estimated propensity score distributions for the sample using the basic matching variables. Panel B reports differences in preevent basic characteristics for this sample. Panel C is a univariate DiD test of the change in Δ*AdjSale* (industry-adjusted sales growth), Δ*MktShr* (market share growth), Δ*Cntrct* (sales contract growth), *ROA* (return-on-assets), and *CFOA* (cash flow-on-assets) from year *t*-1 to year *t* + 1. Panel D is a multivariate DiD test of the change in Δ*AdjSale*, Δ*MktShr*, Δ*Cntrct*, *ROA*, and *CFOA* from year *t*-2 to year *t* + 2 (excluding *t*). Samples in Panel D are populated from those in Panel C but further require both tweeting and control firms to have data available to calculate firm financials in year *t*-2 and *t* + 2. *NPD* equals one for treatment firms and zero for control firms, *POST* equals one for posttreatment periods and zero for pretreatment periods, and *NPD* × *POST* is the DiD estimator. Controls include *Size*, *MB*, *ROA*, and *Lev* in columns (1)–(3) but exclude *ROA* in columns (4) and (5). Panel E reports the mean market- or industry-adjusted CARs to matched non-NPD-tweeting firms surrounding NPDs of tweeting firms. Each column in Panel E tests whether the market- or industry-adjusted CAR is significantly different from zero. Detailed variable definitions are in Appendix A. *p*-values are from the two-tailed tests in Panels A, B, and E and the one-tailed tests in Panels C-D.

5. Additional analyses

The results thus far are consistent with our interpretation that NPDs are positive self-disclosures about the tweeting firms themselves. In this section, we conduct robustness tests (with a focus on conditional samples) and additional analyses using a larger sample to further support this interpretation.

5.1 Robustness tests

The main analyses rely on the financial dictionary of Loughran and McDonald (2011) to define tone. To check for robustness, we redefine the tone of a peer disclosure negative if the news summary contains more negative words than positive words according to at least two of the four commonly used word lists: Loughran and McDonald's (2011) dictionary, Harvard General Inquirer's IV-4 dictionary, Hu and Liu (2014) QDAP dictionary, and Henry's (2008) financial dictionary. We rerun the main analyses in Tables 4–12 (excluding descriptive statistics and robustness checks) using the samples of NPDs under this alternative definition of tone. Tables OA6–OA8 of the Online Appendix present the results, and they are similar to those reported earlier. One exception is that event returns to tweeting firms are more positive surrounding initial news days, even after we exclude NPDs retweeted on the same day.

Next, we rerun the analyses in Tables 10–12 including additional controls. These controls, adapted from Cao et al. (2018), are the focal firm's market capitalization, return and earnings volatility, analyst coverage, institutional holdings, market-to-book, leverage, and an indicator for yearly earnings-per-share increase. Table OA9 of the Online Appendix shows that the coefficient estimates on measures of spillovers remain positive and significant at the 10% level or lower.

We then turn to robustness checks on the calculation of *Tech proximity*. The main specifications in Table 11 calculate the measure for each firm-year using the firm's applied patents accumulated over the past 20 years. While 20 years are the typical term of a US patent, patents filed years ago may be less relevant for the technologies used in the firm's current products. We thus modify *Tech proximity* using applied patents accumulated over the past 18 or 15 years. Table OA10 of the Online Appendix reports results using the two modified measures, and they remain robust.

The final set of tests concerns the definition of conditional sample. In Tables 10–12, we require the peer firm of a firm pair-year to receive at least one NPD to be included in the conditional sample. The advantage of this approach is that it ensures that the peer firm has adverse news that is deemed tweetable by at least one firm in a year. However, this approach may omit firm pair-year observations for which the peer firm has tweetable adverse news but was either not mentioned by any NPD or not captured by our sampling procedure. We thus relax our definition of the conditional sample by keeping all firm pair-year observations in the unconditional sample as long as they are from industries with at least one piece of negative product-related news. We retrieve product-related news from the Capital IQ Key Developments database.[19] Tables OA11 of the Online Appendix repeats the analyses in Tables 10–12 using the redefined samples and reports similar results.

5.2 Analyses with a larger sample

We apply stringent criteria in building the primary sample of NPDs used in our main analyses. Although clean and homogenous, it is admittedly small. To increase sample size, we supplement the primary sample with 639 neutral peer disclosures for which we are able to trace the initial news days and the tweeted firms experience a sizable negative market reaction at the time of initial news release (i.e., CAR [0, +1] over the value-weighted industry portfolio is less than -0.5% with 0 being the initial news day). Thus, instead of using textual analysis to capture the tone of these tweets, we assume that a negative market reaction reflects the adverse nature of the news. As expected, this sample is less homogenous than the primary sample as it covers significantly more NPDs from nontech firms and more nonproduct-market-related news.[20]

We rerun the main analyses using the expanded sample of NPDs. Tables OA12–OA15 of the Online Appendix present the results, and they are similar to those reported in Section 4. One exception is that event returns to tweeted firms are significantly negative surrounding both initial news days and NPD days. While this result may be consistent with either the dissemination hypothesis or the disclosure hypothesis (if the new information released by the tweeting firm via the NPD negatively affects the tweeted firm through spillover effects), we notice that event returns to tweeting firms continue to be much larger surrounding NPD days than surrounding initial news days, which is more consistent with the disclosure hypothesis than the dissemination hypothesis.

6. Conclusion

The advent of social media has revolutionized the way that we communicate. In the corporate world, social media has increasingly become an indispensable tool. Businesses use social media to promote products and services, gage market trends, engage consumers, and offer customer support. Prior studies find that the use of social media, by allowing direct and instant access to a wide audience, facilitates dissemination of firms' own product and financial information (e.g., Blankespoor et al., 2014; Miller and Skinner, 2015; Blankespoor, 2018). This paper shows another corporate use of social media—publicizing adverse news of industry peer firms, or NPDs.

In our main analyses, we study a sample of 649 NPDs issued in the form of tweets between 2009 and 2017,

[19] One caveat is that the Capital IQ Key Developments database collects news from major sources that are different from the news sources that we report in Table 2, Panel A. Thus, it may not be a comprehensive source for NPD tweetable news.

[20] For nontech firms, there could exist a spillover similar to the technology spillover through which firm *j*'s news affects firm *j* and firm *i* in the same direction, for example, because two firms face similar market conditions and regulations.

most of which are linked to peer firms' product market news. Descriptive statistics of these tweets reveal a general increasing trend in the incidence of NPDs over time. NPDs predominantly originate from tech firms, and the news sources for NPDs are also tech heavy. In comparing the tweeting firms of NPDs to the tweeted firms, we notice that tweeted firms tend to be industry leaders, while tweeting firms are younger, smaller, and less established.

We hypothesize that NPDs are firms' implicit positive self-disclosures motivated by the spillover effects from peer firms' adverse news. Consistent with this hypothesis, we find that disclosing firms experience an excess return of 1.6−1.7% over the market and the industry during a two-day event window starting the day of disclosure. The excess returns are similar if computed over the Fama-French characteristic-based portfolios. In exploring the benefits of corporate NPDs, we find that firms' propensity to issue NPDs increases with the intensity of product market rivalry spillover, proxied using either the product proximity measure of BSV or the product similarity measure of HP. The propensity to issue NPDs also increases with the intensity of technology spillover, proxied using the technology proximity measure of BSV. Further, the propensity to issue NPDs decreases with the clarity of spillover links. These results are robust to including various controls and fixed effects and to using alternative dictionaries to capture disclosure tone, alternative measures of spillover strength, and a less homogenous sample of larger size. They shed light on the existence of spillover effects and firms' capability of internalizing these effects. Finally, we find that NPD-tweeting firms outperform non-NPD-tweeting peer firms with similar preevent characteristics. These results shed light on the disclosure costs of corporate NPDs.

We believe that the study of peer disclosures is likely a fruitful area for future research. As a modest first step, this paper has limitations. First, our primary sample includes only 649 tweets, and the expanded sample roughly doubles in size. These two samples need not reflect the entire population of NPDs as such disclosures may be issued through other venues or even intermediaries. For example, a recent Wall Street Journal article reports that some of Amazon.com Inc.'s biggest rivals—Walmart Inc., Oracle Corporation, and Simon Property Group—are secret funders of a nonprofit group that has used both political and social media tools in a national campaign criticizing Amazon's business practices.[21] Nevertheless, our inferences are likely valid only to the extent that our sample is representative. Second, while our results are more consistent with the disclosure hypothesis, we cannot rule out the dissemination hypothesis that could very well apply in certain NPDs. Finally, our study is restricted to negative peer disclosures, leaving nonnegative peer disclosures unattended. Why some firms issue positive and neutral peer disclosures is an intriguing question that is beyond the scope of this study. The limitations of our study open up opportunities for future studies, especially if more creative methods of collecting peer disclosures emerge.

Appendix A: Variable definitions

This appendix describes the calculation of variables used in the main analyses. Underlined variables refer to variable names within Compustat. *i* denotes the focal firm, which decides whether to issue NPDs upon receiving the news; *j* denotes the peer firm; and *t* denotes the fiscal year during which a tweet is issued for firm *i* and *j*.

[21] See James Grimaldi, "A 'grass roots' campaign to take down Amazon is funded by Amazon's biggest rivals," the Wall Street Journal, September 20, 2019.

Variable	Definition
Firm characteristics reported in the descriptive analyses (for both firm i and firm j)	
Age_t	Firm's age in year *t*, approximated by the number of years listed on Compustat.
$Size_t$	Natural logarithm of market value of equity (*PRCC_F* × *CSHPRI*) at the end of year *t*.
$Asset_t$	Natural logarithm of book value of total assets at the end of year *t* (*AT*).
MB_t	Market-to-book, calculated as market value of equity divided by book value of common equity (*CEQ*) at the end of year *t*.
ROA_t (ROA_{t-1}, ROA_{t+1})	Return-on-assets, calculated as net income (*NI*) during year *t* divided by the average of the beginning and ending total assets of year *t*. ROA_{t-1} and ROA_{t+1} are return-on-assets of year t-1 and year $t+1$, respectively.
Lev_t	Book leverage, calculated as book value of debt (*DLTT*+*DLC*) minus balance sheet deferred taxes and investment tax credit (*TXDITC*) and then divided by total assets at the end of year *t*. Missing deferred taxes and investment tax credit is set to zero.
$Cash_t$	Cash and short-term investments (*CHE*) divided by total assets at the end of year *t*.
Capex intensity$_t$	Capital expenditure (*CAPEX*) divided by total sales (*SALE*) during year *t*. Missing capital expenditure is set to zero.
R&D intensity$_t$	R&D expenditure (*XRD*) divided by total sales during year *t*. Missing R&D expenditure is set to zero.
Ad intensity$_t$	Advertising expenditure (*XAD*) divided by total sales during year *t*. Missing advertising expenditure is set to zero.
Asset turnover$_t$	Asset turnover calculated as total sales during year *t* divided by the average of the beginning and ending total assets of year *t*.
Past year return$_t$	Compounded market-adjusted monthly stock returns over the 12 months prior to the tweeting month of an NPD for the tweeting and tweeted firms. For benchmark tech firms, this return is calculated over the fiscal year that corresponds to the fiscal year of the tweeting firms.
Variables used in the main analyses	
CAR [*m, n*]	Cumulative abnormal returns (CARs) aggregated from day *m* to *n* surrounding an NPD, where day 0 is either the day of NPD or the first subsequent trading day if an NPD falls on a weekend or a holiday. For market-adjusted CARs, the daily abnormal return is the firm's raw return minus the corresponding return on the CRSP equal- or value-weighted index. For industry-adjusted CARs, the daily abnormal return is the firm's raw return minus the corresponding return on the equal- or value-weighted industry portfolio. Industry is defined based on the TNIC-3 industries. For Fama-French characteristic portfolio-adjusted CARs, the daily abnormal return is the firm's raw return minus the corresponding return on the equal- or value-weighted characteristic-based portfolios. Decile characteristic-based portfolios are formed using the breakpoints downloaded from Kenneth French's data library. These breakpoints are assigned based on univariate sorts on book-to-market (BM), profitability, and investment as well as bivariate sorts on BM and profitability, BM and investment, and profitability and investment. Daily returns are then summed over the event window. *CAR* [*m, n*] surrounding an initial news day is analogously defined, where day 0 is either the initial news day or the first subsequent trading day if the initial news day falls on a weekend or a holiday.
NPD_t	*NPD* is an indicator variable that denotes the existence of an NPD, which equals one if firm *i* posts at least one tweet through its corporate Twitter account disclosing adverse news of peer firm *j* in year *t* and equals zero otherwise.
Prod similarity$_t$	*Prod similarity* is the pairwise product cosine similarity score between firm *i* and firm *j*, calculated based on the unique words that the two firms use to describe their products in their business description sections of 10-K filings (Item 1 or Item 1A), following HP.
Prod proximity$_t$	*Prod proximity* is the pairwise product market closeness measure between firm *i* and firm *j*, calculated as the uncentered correlation between S_i and S_j where S_i and S_j are vectors of firm *i*'s and firm *j*'s share of sales in the four-digit SIC industries, following BSV.
Tech proximity$_t$	*Tech proximity* is the pairwise technology proximity measure between firm *i* and firm *j*, calculated as the uncentered correlation between T_i and T_j where T_i and T_j are vectors of firm *i*'s and firm *j*'s share of patents applied in a patent technology class, following BSV. Patents applied are accumulated for the past 20 years, and technology classes are assigned by the United States Patent and Trademark Office.
Relative size$_t$	*Relative size* is the ratio of firm *i*'s market value of equity to firm *j*'s market value of equity in year *t*.
Relative MB$_t$	*Relative MB* is firm *i*'s market-to-book minus firm *j*'s market-to-book in year *t*.
Relative ROA$_t$	*Relative ROA* is firm *i*'s return-on-assets minus firm *j*'s return-on-assets in year *t*.
Relative lev$_t$	*Relative lev* is firm *i*'s book leverage minus firm *j*'s book leverage in year *t*.
$CFOA_{t-1}$ ($CFOA_{t+1}$)	Cash flow-on-assets, calculated as net operating cash flow (*OANCF*) during a year divided by the average of the beginning and ending total assets of the year. $CFOA_{t-1}$ and $CFOA_{t+1}$ are cash flow-on-assets of year *t*-1 and year $t+1$, respectively.
$SIC3Brdth_t$	*SIC3Brdth*, for each pair of firm *i-j* in year *t*, is the ratio of the number of firms in firm *i*'s three-digit SIC industry to the number of firms in firm *i*'s TNIC-3 industry in the year plus the ratio of the number of firms in firm *j*'s three-digit SIC industry to the number of firms in firm *j*'s TNIC-3 industry in the year divided by two.
$DiffSIC3_t$	*DiffSIC3* is an indicator variable that equals one if a pair of firm *i-j* formed using the TNIC-3 classification falls into different three-digit SIC industries in year *t* and equals zero if the two firms share the same three-digit SIC code.

(*continued on next page*)

(*continued*)

Variable	Definition
$\Delta AdjSale_{t\text{-}1}$ ($\Delta AdjSale_{t+1}$)	Annual growth in industry-adjusted sales, calculated as the change in industry-adjusted sales from year t-1 to year *t* scaled by industry-adjusted sales in year *t*-1. A firm's industry-adjusted sales is the firm's annual total sales minus industry median sales in a given year. $\Delta AdjSale_{t\text{-}1}$ and $\Delta AdjSale_{t+1}$ are annual growth in industry-adjusted sales of year *t*-1 and year $t + 1$, respectively.
$\Delta MktShr_{t\text{-}1}$ ($\Delta MktShr_{t+1}$)	Annual growth in market share, calculated as the change in market share from year *t*-1 to year *t*. A firm's market share is the firm's total sales as a percentage of the industry's total sales in a given year. $\Delta MktShr_{t\text{-}1}$ and $\Delta MktShr_{t+1}$ are annual growth in market share of year *t*-1 and year $t + 1$, respectively.
$\Delta Cntrct_{t\text{-}1}$ ($\Delta Cntrct_{t+1}$)	Annual growth in the number of sales contracts as reported in the FactSet database, calculated as the change in the number of sales contracts from year *t*-1 to year *t* scaled by the number of sales contracts in year *t*-1. $\Delta Cntrct_{t\text{-}1}$ and $\Delta Cntrct_{t+1}$ are annual growth in the number of sales contracts of year *t*-1 and year $t + 1$, respectively.
NPD_i	*NPD* is an indicator variable used in the multivariate DiD test that denotes firms, which equals one if firm *i* issued an NPD and equals zero otherwise.
$POST_t$	*POST* is an indicator variable used in the multivariate DiD test that denotes periods, which equals one if year *t* is after the year during which firm *i* issued an NPD and equals zero otherwise.

References

Aboody, D., Kasznik, R., 2000. CEO stock option awards and the timing of corporate voluntary disclosures. J. Account. Econ. 29, 73–100.

Ali, A., Klasa, S., Yeung, E., 2014. Industry concentration and corporate disclosure policy. J. Account. Econ. 58, 240–264.

Anderson, S., Ciliberto, F., Liaukonyte, J., Renault, R., 2016. Push-me pull-you: comparative advertising in the OTC analgesics industry. Rand J. Econ. 47, 1029–1056.

Anderson, S., Renault, R., 2009. Comparative advertising: disclosing horizontal match information. Rand J. Econ. 40, 558–581.

Aobdia, D., Cheng, L., 2018. Unionization, product market competition, and strategic disclosure. J. Account. Econ. 65, 331–357.

Barigozzi, F., Garella, P., Peitz, M., 2009. With a little help from my enemy: comparative advertising as a signal of quality. J. Econ. Manag. Strategy 18, 1071–1094.

Beyer, A., Cohen, D., Lys, T., Walther, B., 2010. The financial reporting environment: review of the recent literature. J. Account. Econ. 50, 296–343.

Blankespoor, E., 2018. Firm communication and investor response: a framework and discussion integrating social media.. Account. Organ. Soci. 68, 80–87.

Blankespoor, E., Miller, G., White, H., 2014. The role of dissemination in market liquidity: evidence from firms' use of Twitter. Account. Rev. 89, 79–112.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81, 1347–1393.

Cade, N., 2018. Corporate social media: how two-way disclosure channels influence investors. Account. Organ. Soc. 68, 63–79.

Cao, S., Ma, G., Tucker, J., Wan, C., 2018. Technological peer pressure and product disclosure. Account. Rev. 93, 95–126.

Crowley, R., Huang, W., Lu, H., 2018. Discretionary Dissemination On Twitter. Singapore Management University Unpublished Working Paper.

Files, R., 2012. SEC enforcement: does forthright disclosure and cooperation really matter? J. Account. Econ. 53, 353–374.

Foster, G., 1981. Intra-industry information transfers associated with earnings releases. J. Account. Econ. 3, 201–232.

Freeman, R., Tse, S., 1992. A nonlinear model of security price responses to unexpected earnings. J. Account. Res. 30, 185–209.

Gentzkow, M., Kelly, B., Taddy, M., 2019. Text as data. J. Econ Lit. 57, 535–574.

Henry, E., 2008. Are investors influenced by how earnings press releases are written? J. Bus. Comm. 45, 363–407.

Hirshleifer, D., Teoh, S., 2003. Limited attention, information disclosure, and financial reporting. J. Account. Econ. 36, 337–386.

Hoberg, G., Phillips, G., 2010. Product market synergies and competition in mergers and acquisitions: a text-based analysis. Rev. Financ. Stud. 23, 3773–3811.

Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. J. Political Econ. 124, 1423–1465.

Hu, M., Liu, B., 2014. Mining opinion features in customer reviews. In: Proceedings of the 19th National Conference on Artificial Intelligence AAAI, 4, pp. 755–760.

Jung, M., Naughton, J., Tahoun, A., Wang, C., 2018. Do firms strategically disseminate? Evidence from corporate use of social media. Account. Rev. 93, 225–252.

Kim, J., Verdi, R., Yost, B., 2020. Do firms strategically internalize disclosure spillovers? Evidence from cash-financed M&As. J. Account. Res. 58, 1249–1297.

Lau, R., Rovner, I., 2009. Negative campaigning. Annu. Rev. Political Sci. 12, 285–306.

Lee, L., Hutton, A., Shu, S., 2015. The role of social media in the capital market: evidence from consumer product recalls. J. Account. Res. 53, 367–404.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. J. Finance 66, 35–65.

Loughran, T., McDonald, B., 2014. Measuring readability in financial disclosures. J. Finance 69, 1643–1671.

Loughran, T., McDonald, B., 2016. Textual analysis in accounting and finance: a survey. J. Account. Res. 54, 1187–1230.

Miller, G., Skinner, D., 2015. The evolving disclosure landscape: how changes in technology, the media, and capital markets are affecting disclosure. J. Account. Res. 53, 221–239.

Rakowski, D., Shirley, S., Stark, J., 2021. Twitter activity, investor attention, and the diffusion of information. Financ. Manag. forthcoming.

Skinner, D., 1994. Why firms voluntarily disclose bad news. J. Account. Res. 32, 38–60.

Skinner, D., 1997. Earnings disclosures and stockholder lawsuits. J. Account. Econ. 23, 249–282.