Beyond Disclosure: The Social Role of Social Media

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Abstract

This study sheds light on the "social" dimension of social media. We present novel evidence that firms use positive peer tweets as a form of social signaling to indicate economic ties with other firms. By analyzing firms that share positive peer information, we examine the determinants, information content, and capital market consequences of positive peer tweeting. We find that positive peer tweeting is associated with factors such as economic relatedness, the demand for legitimacy, and litigation risk. These tweets predict future inter-firm collaborations, conveying information not readily available in traditional disclosures. Further, positive peer tweets generate significantly positive market reactions for both the tweeting and tweeted firms. However, this social signaling is not without costs: tweeting firms experience negative market reactions when the firms they tweeted about subsequently release negative news. These findings highlight the social role of social media beyond its well-studied disclosure and dissemination roles.

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1. Introduction

One of the fundamental questions in financial economics revolves around how market participants convey and interpret financial information. Social media, which allows user-generated content to be widely and instantly shared, has significantly changed how information is created, disseminated, and used by various capital market participants (Miller and Skinner 2015). Prior studies have shown that firms use social media to disclose and disseminate information to investors and customers (Blankespoor et al. 2014; Lee et al. 2015; Miller and Skinner 2015; Jung et al. 2018). While the literature has extensively studied social media's "media" dimension, i.e., information disclosure and dissemination, the "social" dimension remains unexplored. The social dimension is central to individuals' social media activity. Boyd and Ellison (2007) argue that what makes social unique is that it enables users to articulate and make visible their social connections. We explore whether this social dimension extends to corporate social media activity. Unlike private channels, the public nature of social media content makes it a distinctive platform for firms to signal their social connections, which are observable to all stakeholders. Utilizing a novel sample of firms that share positive information about their peers on social media, we aim to provide the first evidence on corporate social signaling, including its determinants, information content, and capital market consequences.

To capture corporate social signaling, we focus on firms that engage in "positive peer tweeting," i.e., disseminating positive peer information on Twitter (now X). For example, on July 1, 2016, Synchronoss Technologies Inc. (SNCR) tweeted: "@Qualcomm Readies Lower-Band #5G testbed." This example illustrates several defining features of positive peer tweets: (1) the content is favorable to the tweeted firm, Qualcomm, (2) the information is non-financial in nature, (3) the originator of the tweet, Synchronoss, a provider of cloud, digital, and network management

solutions, is related to Qualcomm, a wireless technology provider, along the supply chain. Appendix B provides additional examples of positive peer tweets in our sample. [1]

We posit that positive peer tweets serve as early signals of firms' informal economic ties, particularly when future collaboration remains uncertain, while circumventing potential regulatory or legal complexities associated with traditional disclosure channels, such as press releases and earnings conference calls.[2] However, the informal nature of such signals may cast doubt on their credibility. Ultimately, it remains an empirical question whether positive peer tweets serve as effective signals, i.e., whether they predict future inter-firm collaborations and whether investors respond to such signals.

To construct the sample of positive peer tweets, we begin by identifying pairs of economically related peer firms based on their product market relatedness. Prior studies document that inter-firm economic links generate information exchanges (e.g., Baiman and Rajan 2002; Schloetzer 2012; Arya et al. 2019), and such inter-firm economic links can arise from both horizontal relationships in product markets and vertical relationships along supply chains. Therefore, we consider both same-industry (i.e., horizontal) and supply-chain (i.e., vertical) relationships when forming economically related firm pairs. Next, we require both firms in each pair to have verified Twitter accounts. We then search for peer disclosure tweets between these firm pairs from January 1, 2008, to December 31, 2023. Finally, we classify positive peer tweets

[1] Positive peer tweets are not the only social signals that can indicate corporate ties. Corporate following of other corporations on Twitter can serve as another potential signal. However, using corporate following has limitations. For instance, some corporations, such as Apple, do not follow other corporations. Additionally, historical following or unfollowing activity is not available, and only the current state of "following" list is observable. These limitations reduce the power of empirical analyses utilizing such data.

[2] Corporate press releases are typically self-disclosures. While firms can mention peer firms during earnings conference calls (Brochet et al. 2018), earnings calls may lack timeliness, and questions about specific peer firms may not always arise during a call.

based on the sentiment of the tweet content. Following this procedure, we compile a sample of 6,233 positive peer tweets with available stock trading information.

Our empirical analysis begins by examining the characteristics of firms that post positive peer tweets (i.e., tweeting firms) and the firms that are the subjects of such tweets (i.e., tweeted firms). We find that both tweeting and tweeted firms are frequently from high-tech industries. Positive peer tweets occur between both horizontal industry peers and vertical supply chain peers. Notably, the firms being tweeted about tend to be more established and profitable, including firms such as Microsoft and Intel.

We conjecture that positive peer tweets are more likely to occur among firms with stronger ties and whose fortunes tend to move in sync. Indeed, we find that firms that share common institutional blockholders and exhibit higher stock return correlations are more likely to post positive tweets about each other. While industry leaders are active as both tweeting and tweeted firms in positive peer tweets, they are three to four times more likely to be mentioned in such tweets than to tweet about other peer firms. Larger firms are also more likely to be the subjects of positive peer tweets. These results are consistent with the motivation of tweeting firms to enhance their legitimacy and status by signaling economic ties with prominent and highly visible firms. Finally, given the high shareholder litigation risk associated with formal firm disclosures (Rogers et al. 2011; Cazier et al. 2020), positive peer tweets may serve as a low-risk alternative for firms to provide early signals of potential inter-firm collaborations without increasing their legal exposure. Consistent with our expectations, the likelihood of positive peer tweets is positively associated with the litigation risk of both the tweeted and tweeting firms. Overall, our evidence suggests that positive peer tweets are associated with inter-firm relatedness, product market power, and expected litigation risk.

Next, we examine the information content of positive peer tweets, specifically whether they signal stronger future economic ties between the tweeted and tweeting firms, such as potential future collaborations. Since our sample includes both horizontally- and vertically-related peers, we consider future inter-firm collaborations in product markets and along supply chains. We find strong evidence that the frequency of positive peer tweets is positively associated with the likelihood of the tweeting and tweeted firms becoming strategic alliance partners or supply chain partners in the next three years, after controlling for the characteristics of both firms, and firm pair and year fixed effects. In terms of economic magnitude, a one-standard-deviation increase in positive peer tweets for a given firm pair-year translates to a 6.7-24.2% increase in the likelihood of establishing a new collaborative relationship in the next three years. These results suggest that positive peer tweets can serve as a valuable signal of future product market collaborations.

In addition to forming new relationships, firms with existing partnerships may expand their collaborations. We hypothesize that positive peer tweets between collaborating firms indicate the potential expansion of their current relationships. Using a sample of supplier-customer firm pairs with available inter-firm sales data from Compustat Segments, we find that the number of positive peer tweets is positively associated with increased future sales between the two firms. Specifically, the more frequent the positive peer tweets between two firms, the greater the customer's average share of total sales from the supplier firm in the next three years. This finding suggests that positive peer tweets not only signal new collaborations among firms but also the expansion of existing collaborations.

After documenting that positive peer tweets signal future economic ties, we turn to how investors perceive and react to positive peer tweets. We examine the market reactions to positive peer tweets for both tweeted and tweeting firms. It is perhaps not surprising that tweeted firms

experience a positive market reaction on the day of the positive peer tweets. These tweets are likely prompted by good news at the tweeted firms, and they further disseminate and broaden the reach of the positive information. In line with our expectation, we find that a tweeted firm, on average, experiences a positive market-adjusted cumulative abnormal return (CAR) of 10-11 basis points (0.10-0.11%) on the tweeting day (roughly 29% on an annualized basis), 14 basis points over the [0, 1] two-day window, and 17 basis points over the [0, 2] three-day window.[3]

In contrast to the positive market reaction for tweeted firms, it is less clear whether investors will react positively to *tweeting* firms, as they merely share positive news about a peer firm rather than about themselves. However, if investors view positive peer tweets as signals of potentially strengthened future economic ties between the two firms, they may also react positively to the *tweeting* firm. Indeed, this is what we find. The average market-adjusted CAR for tweeting firms is 5-6 basis points on the positive peer tweeting day, approximately half of the CAR for tweeted firms. This translates to an annualized return of roughly 13%.[4] The average market-adjusted CAR for tweeting firms increases to 10-11 points over the [0, 1] two-day window and 18 to 19 points over the [0, 2] three-day window. Interestingly, tweeting firms, despite sharing content not directly related to their own operations, experience positive market reactions along with the tweeted firms. Collectively, these findings are consistent with the idea that the economic ties signaled by positive peer tweets create a spillover effect to the tweeting firm, as the market perceives future product market collaborations with tweeted firms as beneficial to tweeting firms.

We conduct additional analyses to strengthen our inference regarding the signaling value of positive peer tweets. First, we perform a falsification test to confirm that positive market returns

[3] The event day CAR of 10 basis points annualized = $(1.0010)^{252} - 1 \approx 29\%$.
[4] The event day CAR of 5 basis points annualized = $(1.0005)^{252} - 1 \approx 13\%$.

accrue specifically to firms engaging in positive peer tweets, rather than to any peer firms that benefit from the positive spillovers from the tweeted firm. Specifically, we examine market reactions to *non-tweeting* peer firms around positive peer tweets. In contrast to the results for tweeting firms, we find no abnormal market reaction for these non-tweeting peer firms, confirming the unique signaling value of positive peer tweets.

Next, we investigate whether investors anticipate the likelihood of potential inter-firm collaborations implied by positive peer tweets and impound the information in their reactions. We begin by documenting that investor reactions to positive peer tweets vary with eventual collaboration outcomes: the market reacts more positively to positive peer tweets that are followed by subsequent inter-firm collaborations. This evidence directly links investor reactions induced by positive peer tweets to collaboration outcomes. Furthermore, we examine the relationship between positive peer tweets and investors' reactions to subsequent announcements of strategic alliances between the tweeted and tweeting firms. If investors interpret positive peer tweets as signals of future collaborations, the anticipation effect will reduce the surprise component of subsequent collaboration announcements, leading to a smaller market reaction. When we compare the market-adjusted CARs around strategic alliance announcements preceded by positive peer tweets to those without such tweets, we find that positive peer tweets dampen the positive market reactions to subsequent strategic alliance announcements. This provides further evidence consistent with the signaling role of positive peer tweets.

The finding that positive abnormal returns accrue to firms posting positive peer tweets raises the question: do tweeting firms incur any cost by posting positive peer tweets? We conjecture that signaling economic ties is not costless, as tweeted firms' subsequent negative news can spill over to tweeting firms. To test this prediction, we focus on an adverse information event for

tweeted firms: negative management earnings guidance. We examine the market reactions to *tweeting* firms around the tweeted firm's subsequent negative earnings guidance. The analyses show that when a tweeted firm issues negative earnings guidance, peer firms that posted positive tweets about it in the past three months experience lower CARs than those that did not post positive peer tweets. This result suggests that signaling economic ties via positive peer tweets imposes costs on tweeting firms in the form of negative spillovers.

Our study contributes to multiple strands of literature. Our most important contribution is to provide the first insights into the "social" dimension of social media, which goes beyond the well-studied "media" dimension, i.e., disclosure and dissemination (see, e.g., Blankespoor et al. 2014; Lee et al. 2015; Miller and Skinner 2015; Jung et al. 2018). Social signaling can serve as an early indicator of firms' economic ties, while avoiding potential regulatory or legal complexities associated with traditional disclosure channels. We provide novel evidence on how firms use social media to signal their connections and how investors interpret such social signals. This evidence broadens our understanding of the role played by social media as a corporate information channel.

Second, we highlight social media as a rich source of forward-looking and non-financial information. We underscore the unique information value of social signals as forward-looking indicators of future events, such as product market collaborations. This type of information is not readily available from other channels and can be particularly valuable to retail investors by lowering their information acquisition and processing costs (Blankespoor 2019; Blankespoor et al. 2020; deHaan et al. 2023). By shedding light on social media as a source of forward-looking and non-financial information, we complement and extend prior literature that documents social media's role in disclosing and disseminating financial information, such as earnings and sales (e.g., Blankespoor et al. 2014; Bartov et al. 2018; Tang 2018; Cookson et al. 2024).

Finally, our study contributes to the emerging literature on corporate disclosure about peer firms (Brochet et al. 2018; Kim et al. 2020; Cao et al. 2021; Bloomfield et al. 2024). While previous studies tend to focus on negative peer disclosures, we study the implications of positive peer disclosures. While both pertain to peer firms, positive and negative peer disclosures are empirically distinct and driven by different economic forces. Negative peer disclosures are motivated by firms' desire to highlight their own superiority (Cao et al. 2021) or to harm other firms' strategic positions (Kim et al. 2020; Bloomfield et al. 2024). In contrast, firms share favorable news about peer firms to signal closer economic ties and potential future collaborations.

2. Sample, Data, and Descriptive Statistics

We follow a three-step process to construct the sample of positive peer tweets used in our primary analyses. First, we construct a set of peer firm pairs. Prior studies document that inter-firm economic links generate information exchanges (Baiman and Rajan 2002; Schloetzer 2012; Arya et al. 2019; Crawford et al. 2020). Such inter-firm economic links can arise horizontally in product markets and vertically along supply chains. To identify horizontal peer firms in product markets, we use the time-varying firm-specific text-based network industry classification (TNIC) and focus on firms in the same TNIC-3 industry (Hoberg and Phillips 2010, 2016). This classification has the advantage of identifying closely related firms in rapidly evolving product markets. For vertical peer relationships along supply chains, we consider a pair of firms to be vertically related if any firm in one firm's industry has at least two suppliers or customers in the other firm's industry (Cao et al. 2024). Since this method requires transitive industry classifications, we define industries based on the Standard Industrial Classification (SIC) four-digit system. We obtain supplier-customer relationship data from Compustat Segments and FactSet Revere Supply Chain Relationships.

Second, for every firm assigned to a pair, we manually search for its Twitter (now X) account on its corporate website (e.g., Nekrasov et al. 2022). If multiple accounts are listed, we use the one that represents the entire firm or corporate headquarters. We retain firm pairs where both firms have verified Twitter accounts, resulting in 351,788 unique peer firm pairs consisting of 4,012 unique firms. We then search for peer tweets posted between these pairs from January 1, 2008, to December 31, 2023, following the procedure outlined by Cao et al. (2021). Specifically, for a given pair of firm *i*-*j*, we search tweets posted by firm *i* (*j*) that mention firm *j* (*i*). To ensure the tweets contain meaningful news, we require all tweets to include a hyperlink to news sources. This step yields 38,068 peer tweets posted between 5,810 firm pairs.

Third, we identify positive peer tweets based on the tone of their content. A tweet typically summarizes news in the tweeting firm's own language and its tone reflects the sentiment that the firm seeks to express in the tweet (Cao et al. 2021). A peer tweet is classified as a positive peer tweet if the tweet contains more positive words than negative words, as defined by Loughran and McDonald (2011). Using this tone-based approach, we classify 6,233 peer tweets as positive peer tweets with available CRSP return information, from 2008-2023.[5,6] Appendix B presents thirteen examples of positive peer tweets in our sample.

In Figure 1, Panel A (B), we plot the pie chart illustrating the sample distribution by SIC four-digit industry sectors of tweeting (tweeted) firms. We do not rely on TNIC here since TNIC is a firm pair classification system and varies with each firm pair-year. As Figure 1 shows,

[5] We exclude 304 tweets from media companies (e.g., TheStreet, Inc.) as their tweets are part of their core business activities rather than online socializing efforts.

[6] Negative peer tweets are uncommon among the firm pairs in our sample. In our main sample of positive peer tweets (~6,233 tweets), there are 2,490 unique tweeting and tweeted firm pairs, of which only 136 also have negative peer tweets.

technology firms (e.g., computer, software, semi-conductor, etc.) are the most frequent posters and receivers of positive peer tweets.

In Table 1, Panel A, we tabulate the top ten tweeting industries and their corresponding top three tweeted industries in our sample, based on the SIC four-digit industry classification. The results suggest that positive peer tweets exist in both vertical and horizontal peers. Table 1, Panel B lists the top ten tweeting and tweeted firms in our sample. Both tweeting and tweeted firms are frequently from technology-related industries. The tweeted firms include established and highly visible firms such as Microsoft, IBM, and Intel.

Table 2, Panel A presents the summary statistics of the tweeting firms in our primary sample, and Panel B presents the summary statistics for the tweeted firms. Panel C presents pairwise mean comparisons of the tweeting and tweeted firms. Compared to the tweeted firms, the tweeting firms are smaller in terms of total assets (23,249 vs. 80,401 $m) and less profitable, as measured by both loss occurrence and return on assets (0.320 vs. 0.166; -0.004 vs. 0.048). However, these two sets of firms exhibit similar levels of sales growth rate, asset tangibility, financial leverage, and research and development (R&D) expenditures in terms of relative magnitudes.

3. Determinants of Positive Peer Tweets

In this section, we explore the factors that influence positive peer tweets. We explore four sets of firm characteristics likely associated with positive peer tweets: (1) the economic closeness of the firms, (2) product market power dynamics, (3) litigation risk, and (4) firm performance.

First, the closeness between the two firms in the product and capital markets can influence firms' tendency to post positive peer tweets. Firms operating in the same product market have more opportunities for collaboration (MacKay and Phillips 2005; Bills et al. 2020; Cho and Muslu 2021) and, therefore, could have greater incentives to engage in positive peer tweeting. However, it is

also possible that these firms are less likely to post positive peer tweets because the peer firms could be competitors. To capture the economic ties of each firm pair, we calculate the pairwise correlation of their monthly stock returns over the past three years (*Stock Return Corr*) (e.g., Kim et al. 2020).[7] We posit that a firm pair whose fortunes move together has a greater potential for mutually beneficial collaborations, increasing their likelihood of positive peer tweeting. Moreover, recent studies have documented the effect of common institutional blockholders on product market strategies of portfolio firms (He and Huang 2017; Lopez and Vives 2019; Pawliczek et al. 2022). We expect that firms sharing common blockholders are more likely to tweet positive news about each other to maximize portfolio values. *Common Owner* is defined as the number of common institutional blockholders shared by the firm pair during the year, where common institutional blockholders are defined as institutional investors concurrently holding at least 5 percent equity stakes in both firms (Gilje et al. 2020; Peng et al. 2023).

Second, prior studies document that power dynamics in product markets influence firm disclosure decisions (Li 2010; Bernard 2016). Firms often seek to enhance legitimacy and credibility by aligning themselves with industry leaders (Suchman 1995; Brown et al. 2018; De Franco et al. 2023). Consistent with this reasoning, we conjecture that firms have incentives to post positive peer tweets to signal their close ties with industry leaders, bolstering their legitimacy and credibility. At the same time, industry leaders might also use positive peer tweets to promote less prominent potential business partners. Following prior studies (e.g., Porter 1979; Jiang et al. 2015), we define industry leadership status based on market shares. *Firm 1 Leader* (*Firm 2 Leader*) is an indicator variable that equals one if the potential tweeting (tweeted) firm is among the top

[7] In untabulated analysis, our results are similar if we construct *Stock Return Corr* using monthly stock returns during the past year or over the entire sample period.

five largest firms based on sales revenue within each SIC two-digit industry-year. In addition to the industry leadership status of tweeting and tweeted firms, we also construct a measure of a tweeted firm's market power relative to the tweeting firm. *Ln (Firm 2/Firm 1 Market Cap)* is the natural logarithm of the ratio of the tweeted firm's market capitalization to the tweeting firm's market capitalization.

Third, firms' disclosure decisions are influenced by expected litigation risk (Francis et al. 1994; Skinner 1994; Skinner 1997; Field et al. 2005). Since shareholder litigation often targets firm disclosures (Rogers et al. 2011; Cazier et al. 2020), firms facing high litigation risk tend to exercise greater caution when disclosing uncertain information through formal channels. In such cases, positive peer tweets may serve as a low-risk alternative for firms to provide early signals of potential future collaborations without directly increasing their legal exposure. Thus, we expect the likelihood of positive peer tweets to increase for both high-risk tweeting and tweeted firms, provided that the tweeting firms accommodate and internalize the preferences of the tweeted firms. We measure firms' shareholder litigation risk using two approaches. First, we employ the litigation risk model in Kim and Skinner (2012, Table 7, Model 3) (*Lit Risk KS*), consistent with prior studies (e.g., Cao and Narayanamoorthy 2014; Donelson et al. 2022). Second, we measure litigation risk as the natural logarithm of one plus the total number of plaintiff-lawyer EDGAR views of the firm's SEC filings during the prior year (*Lit Risk KY*), following Kartapanis and Yust (2024).

Lastly, it is plausible that firms share positive peer tweets to maintain and signal good relationships with well-performing firms. To investigate this possibility, we examine whether tweeted firms exhibit superior financial performance. Specifically, we measure firm financial performance using an indicator for losses (*Firm 2 Loss*) and return on assets (*Firm 2 ROA*).

To examine the determinants of positive peer tweets, we start with 351,788 unique peer firm pairs, as described in Section 2, and construct a firm pair-year sample from 2008 to 2023. After dropping firm pair-years with missing data and firms in the financial industries (i.e., SIC codes 6000-6999), our sample consists of 1,532,284 firm pair years when using the Kim and Skinner (2012) litigation risk measure (*Lit Risk KS*). The sample is further reduced to 931,198 firm pair-year observations when using the plaintiff-attention-based litigation risk measure (*Lit Risk KY*), which is available only through 2017. Using these two samples, we estimate a linear probability model using Eq. (1) as follows:

$$Peer\ Tweet\ Dummy_{i,j,t} = \alpha + \beta_k Determinants_{i,j,t} + FE + \epsilon_{i,j,t} \quad (1)$$

where *Peer Tweet Dummy* is an indicator variable that equals one when there is at least one positive peer tweet between a pair of firms *i* and *j* in year *t*. *Determinants* is a vector of determinants as discussed above. We include industry × year fixed effects for both firms in the firm pair, which control for time-varying industry factors that might influence positive peer tweeting behavior. We cluster standard errors by both firms in the firm pair.

Table 3 presents the results of the regression analyses. The measure of ex-ante litigation risk is *Lit Risk KS* in column 1 and *Lit Risk KY* in column 2. The inferences are similar across both columns. Firm pairs with more positive stock return correlations and common blockholders are more likely to post positive tweets about each other, confirming that tweeting and tweeted firms are closely related and have potential collaborative opportunities.

We also find that industry leaders are prominent as both tweeting and tweeted firms in positive peer tweets. Notably, the probability of industry leaders being mentioned in positive peer tweets is three to four times higher than the likelihood of industry leaders tweeting about other

firms.[8] The significantly positive coefficient on *Ln (Firm 2/Firm 1 Market Cap)* also suggests that larger firms are more likely to be the subject of positive peer tweets. The findings are consistent with tweeting firms enhancing their legitimacy by signaling their economic relatedness to more successful firms.

Moreover, consistent with our expectations, the likelihood of positive peer tweeting increases when either the tweeted or the tweeting firms face high shareholder litigation risk. Specifically, we find that tweeted firms with higher litigation risk are more likely to receive positive peer tweets, as the coefficient on the litigation risk of firm 2 (i.e., the tweeted firm) is positive and significant across both measures of litigation risk. This suggests that, rather than self-disclosures, high-risk firms may rely on positive tweets from their peer firms as an alternative channel to signal future inter-firm collaborations. While the tweets are initiated by the tweeting firms, the preferences of the tweeted firms are likely accommodated and internalized by the tweeting firms. We also find weak evidence (column 2) that firms facing higher litigation risk are more inclined to post positive peer tweets, supporting the notion that firms strategically use such tweets to signal potential collaborations while mitigating the heightened litigation risk associated with formal disclosures.

Finally, the evidence regarding the financial performance of tweeted firms is mixed and inconsistent. The coefficients on *Firm 2 Loss* and *Firm 2 ROA* are both negative and significant. Firms that experience losses are less likely to be the targets of positive peer tweets, suggesting a positive association between firm performance and being the subject of positive peer tweets. However, firms with high ROAs are less likely to receive positive peer tweets, contradicting the

[8] In column 1, the coefficient on *Firm 2 Leader* is 0.004, and the coefficient on *Firm 1 Leader* is 0.001, so the relative heightened likelihood is 0.004/0.001 - 1 = 3.

earlier evidence. This inconsistency suggests that the financial performance of tweeted firms is unlikely a primary driver of firms' decisions to engage in positive peer tweeting.

In addition to the above factors, we control for both the tweeting and tweeted firms' other fundamentals, including the market-to-book ratio (*MTB*) and sales growth rate (*Sale Growth*). We also control for a firm's "social" tendency, i.e., how frequently it mentions other firms on social media. To measure a firm's social tendency, we use the total volume of tweets about peers, regardless of sentiment, posted by the firm over the previous year (*Tweet Intensity*). Not surprisingly, positive peer tweets are more likely among sociable firm pairs, where either the tweeting firm or the tweeted firm actively engages in peer-related social media activity.

4. Positive Peer Tweets and Future Collaborations

In this section, we explicitly examine the information content of positive peer tweets, specifically, whether they signal potential future collaborations between tweeted and tweeting firms. Given that we consider both horizontal and vertical relationships when forming firm pairs, we examine whether positive peer tweets *predict* subsequent inter-firm collaborations in the product markets and along the supply chains. To implement this test, we construct two firm pair-year samples from 2008-2023. Since we are interested in predicting new collaborations, we exclude firm pair-year observations after the initiation of a collaboration relationship between two firms. The first sample (full sample) consists of 1,936,078 firm pair-year observations.[9] The second sample (conditional sample) includes 58,974 firm pair-year observations of firm pairs that have posted at least one positive peer tweet during the entire sample period. We estimate a linear probability model using Eq. (2) as follows:

[9] The sample size is larger than the sample in Table 3 because of the data availability of control variables.

$$Form\ Relation_{i,j,t} = \alpha + \beta_1 Peer\ Tweet\ Num_{i,j,t} + \beta_k Controls_{i,j,t} + FE + \epsilon_{i,j,t} \quad (2)$$

In Eq. (2), *Form Relation* is an indicator variable that equals one if a pair of firms *i-j* establishes a new collaboration relationship within the next three years (i.e., year *t+1* to year *t+3*).[10] To capture horizontal and vertical inter-firm collaborations, we use strategic alliance information from the Securities Data Company (SDC) Platinum (e.g., Robinson 2008; Ozmel et al. 2013) and customer-supplier relationship data from Compustat Segments and FactSet Revere Supply Chain Relationships. *Peer Tweet Num* is the number of positive peer tweets between firm *i* and firm *j* in year *t*, posted by either firm *i* or firm *j*. *Controls* includes a set of control variables related to the characteristics of firm *i* and firm *j*, including firm size (*Asset Ln*), sales growth rate (*Sale Growth*), loss occurrence (*Loss*), return on assets (*ROA*), leverage (*Lev*), and research and development intensity (*R&D*).

The results are presented in Table 4, Panel A. Columns 1-2 report the results based on the full sample. Column 1 includes year and firm fixed effects and column 2 includes year and firm pair fixed effects. Column 3 reports the results based on the conditional sample, using year and firm fixed effects, and column 4 reports the results using year and firm pair fixed effects. Standard errors are clustered by both firms in each firm pair in all columns.

The coefficients on *Peer Tweet Num* are consistently positive and statistically significant across all four specifications, suggesting positive peer tweets signal future strategic alliance and supply chain collaborations within each firm pair. In terms of economic significance, the results in column 1 indicate that a one standard deviation increase in *Peer Tweet Num* is associated with a 24.2% relative increase in the likelihood of forming a new collaborative relationship in the next

[10] In untabulated analysis, our results are consistent if we define *Form Relation* as one if a new collaboration relationship is established in the next year or two years.

three years.[11] The magnitude of the coefficient on *Peer Tweet Num* in column 2 decreases when firm pair fixed effects are included: a one standard deviation increase in *Peer Tweet Num* corresponds to an 8.8% relative increase in the probability of forming a new collaboration. The results for the conditional sample, consisting of firms which have posted at least one positive peer tweet during the sample period, are consistent with those estimated in columns 1-2. Specifically, in columns 3-4, the economic significance of the coefficients on *Tweet Peer Num* is comparable to those estimated in columns 1-2: 17.9% in column 3 and 6.7% in column 4. These findings highlight that positive peer tweets can predict the formation of inter-firm collaborations.

Given that we also observe positive peer tweets between firms with existing collaborations, we next investigate what these positive peer tweets signal for such firm pairs. We hypothesize that positive peer tweets between collaborating firms indicate the potential expansion of their existing collaborations. To test this prediction, we focus on a sample of supplier-customer pairs with available inter-firm sales data, which allows us to quantify the scope of collaborations between firms along the supply chain.[12] Specifically, we measure the closeness of the collaboration relationship between a customer-supplier pair using the average percentage of sales from the supplier firm to the customer firm in the next three years (i.e., year $t+1$ to year $t+3$) (*Sales Percent*). We regress the percentage of sales between the two firms (from firm i to firm j or from firm j to firm i) on the number of positive peer tweets between this firm pair i-j in year t, as shown in Eq. (3). We employ an unconditional sample consisting of 11,402 firm pair-year observations for customer-supplier pairs and a conditional sample consisting of 2,928 firm pair-year observations of firm pairs that have posted at least one positive peer tweet during our entire sample period.

[11] The mean value of *Form Relation* is 0.012. The standard deviation of *Peer Tweet Num* is 0.132. Thus, the economic magnitude is $0.022 \times 0.132 \div 0.012 = 24.2\%$.

[12] In this test, we do not include strategic alliances as there is no available data to measure the intensity of existing strategic alliance relationships.

$$Sales\ Percent_{i,j,t} = \alpha + \beta_1 Peer\ Tweet\ Num_{i,j,t} + \beta_k Controls_{i,j,t} + FE + \epsilon_{i,j,t} \quad (3)$$

The results are presented in Table 4, Panel B, with standard errors clustered by both firms in each firm pair. Similar to Table 4 Panel A, columns 1-2 report the results based on the full sample and columns 3-4 report the results based on the conditional sample. Year and firm fixed effects are included in columns 1 and 3; year and firm pair fixed effects are included in columns 2 and 4. The coefficients on *Peer Tweet Num* are significantly positive across all four specifications, supporting the conjecture that positive peer tweets signal the potential expansion of existing collaborations. Economically, the coefficient in column 4 suggests that a one standard deviation increase in *Peer Tweet Num* (~0.763) is associated with an increase in inter-firm sales of 0.267 percentage point, equivalent to 1.5% of the mean of *Sales Percent*. Overall, the positive peer tweets signal not only future collaborations among firms without existing collaborations but also the future expansion of collaborations among firms that are already collaborating.

5. Capital Market Consequences of Positive Peer Tweets

The previous analyses provide evidence that positive peer tweets signal future or expanded inter-firm connections. In this section, we examine the capital market consequences of positive peer tweets, specifically how investors react to these social signals.

5.1 Market Reactions to Tweeted and Tweeting Firms

We start by examining market reactions to both tweeted and tweeting firms around the days when positive peer tweets occur. Positive peer tweets likely generate positive market reactions for tweeted firms for a few reasons. First, the positive tweets are likely triggered by positive developments or favorable news at the tweeted firms. Second, positive peer tweets help disseminate favorable information about the tweeted firms. Additionally, such tweets signal

potential future inter-firm collaborations, which could also contribute to positive market reactions for the tweeted firms.

Table 5, Panel A reports the mean market-adjusted CARs for tweeted firms around the days of positive peer tweets. The results suggest that, on average, a tweeted firm experiences an abnormal return of 0.11 percent over the equal-weighted market portfolio and 0.10 percent over the value-weighted market portfolio on the day of the tweet. These returns translate to annualized returns of approximately 29-32%.[13] The two-day and three-day CARs, measured from the tweeting day, increase to 0.14 (0.14) percent and 0.17 (0.17) percent over the equal- (value-) weighted market portfolios, respectively. All of these CARs are statistically significant at the 1% level. For a tweeted firm with the average market capitalization in our sample (~$87,225 million) in our sample, the three-day CAR corresponds to an increase in firm value of $150 million.[14]

While the positive market reaction to the tweeted firms might be expected, it is less clear how investors will react to a tweeting firm, given that the positive developments or favorable news primarily pertain to the tweeted firm. However, if positive peer tweets signal potential future inter-firm collaborations, investors may react positively to the tweeting firm as well. Further, if positive peer tweeting signals strengthened inter-firm connections, the favorable news at the tweeted firm can create a spillover effect that also benefits the tweeting firm.

Table 5, Panel B reports the mean market-adjusted CARs for tweeting firms around the days of positive peer tweets. Interestingly, we find that tweeting firms also experience positive abnormal returns around the tweeting days. They experience an average CAR on the tweeting day of 0.06 (0.05) percent over the equal- (value-) weighted market portfolios (roughly 13-16%

[13] The event day CAR of 10 basis points translates to an annualized return of $(1.0010)^{252} - 1 \approx 29\%$.
[14] Based on column 1 in Table 5, Panel A, for a tweeted firm of average market capitalization (~$87,224.564 million), the increase in firm value is calculated as $87,224.564 million × 0.1719% = $150 million.

annualized), approximately half of the average CAR for tweeted firms on the same day.[15] They experience an average CAR of 0.10-0.11 percent over the two-day window [0, 1] and 0.18-0.19 percent over the three-day window [0, 2]. For a tweeting firm with the average market capitalization in our sample (~$17,205 million), the three-day CAR corresponds to an increase in firm value of $31-32 million. In contrast, the CARs prior to the tweeting day [-1, -1] are statistically indistinguishable from zero, mitigating the concern that the observed positive stock returns are driven by concurrent events at the tweeting firm. The findings suggest that investors respond positively to the social signal sent by the tweeting firm, likely because they interpret it as an indication of a higher likelihood of future inter-firm collaborations. Additionally, investors may anticipate that the tweeted firms' favorable news can also benefit the tweeting firms.

We interpret the positive abnormal returns for both tweeted and tweeting firms as evidence that investors react to the social signals associated with positive peer tweeting. However, a potential concern is that the favorable news about tweeted firms may spill over to all peer firms, regardless of whether these peer firms engaged in positive peer tweeting. To address this concern, we conduct a falsification test by examining the market reactions to non-tweeting peer firms around the days of positive peer tweets. Specifically, for each peer tweet in our sample, we randomly select one of the tweeted firm's peer firms that did not tweet about the tweeted firm. Table 5, Panel C presents the results of this falsification test. In contrast to the evidence in Panel B, non-tweeting peer firms do not experience significant market reactions around the positive tweeting days.[16] This result mitigates the concern that the observed positive stock market reactions

[15] The event day CAR of 5 basis points translates to an annualized return of $(1.0005)^{252} - 1 \approx 13\%$.

[16] In untabulated analysis, we examine market reactions to both tweeting firms and non-tweeting peer firms using a regression framework. Specifically, for each tweet, we include the tweeting firm and randomly select one non-tweeting peer firm. After controlling for year, SIC two-digit industry, and tweet fixed effects, we find consistent evidence that tweeting firms experience significantly positive market reactions on days with positive tweets, relative to their non-

to tweeting firms are driven by the spillover effects from the tweeted firms to all peer firms. Instead, it confirms our earlier interpretation that the market reactions are specifically tied to the social signaling conveyed through positive peer tweets.

5.2 Market Anticipation of Potential Inter-Firm Collaborations Implied by Positive Peer Tweets

So far, we have demonstrated that positive peer tweets signal increased future inter-firm collaborations between tweeted and tweeting firms, and that investors respond positively to these signals for both the tweeting and tweeted firms. To strengthen our inference that positive peer tweets provide early signals of future inter-firm collaborations, we conduct two additional analyses to directly examine the anticipatory effects of positive peer tweets, specifically, whether investors anticipate the potential inter-firm collaborations implied by such tweets.

First, we examine whether the market reactions to positive peer tweets vary with subsequent collaboration outcomes. If the market can evaluate the likelihood of the future inter-firm collaborations implied by positive peer tweets, we should observe more positive marker reactions in cases where inter-firm collaborations subsequently materialize. To test this conjecture, we use our main sample of 6,233 positive peer tweets to estimate the following regression model:

$$Ret\ tweet_{i,j,x} = \alpha + \beta_1 Future\ Collaboration_{i,j,x} + FE + \epsilon_{i,j,x} \quad (4)$$

Ret tweet represents the total market-adjusted CARs for the tweeted firm *i* and tweeting firm *j* on the date of positive peer tweet *x*. *Future Collaboration* is an indicator variable equal to one if the firm pair forms a new collaboration relationship (i.e., becomes strategic alliance partners or supply chain partners) within three years after positive peer tweet *x*, and zero otherwise. The three-year

tweeting peers. In contrast, non-tweeting peer firms, as indicated by the constant term, exhibit no significant market reaction.

time window is consistent with the time frame in the tests of future product market collaborations in Section 4.

As earlier tests suggest that positive market reactions to tweeted and tweeting firms start on the tweeting date, we focus on [0, 0] window to construct *Ret tweet* in Eq. (4). Specifically, we compute the summation of CARs to the tweeted and tweeting firms on their positive peer tweeting date, adjusted by the value-weighted market portfolio (*[0, 0] Ret VW tweet*). We also construct a similar measure adjusted by the equal-weighted market portfolio (*[0, 0] Ret EW tweet*). Consistent with our firm pair level tests in previous sections, we cluster standard errors by both tweeting and tweeted firms.

Table 6, Panel A presents the results from estimating Eq. (4), using tweeting-day CARs over the value-weighted (columns 1-2) or equal-weighted (columns 3-4) market portfolios as dependent variables. We include year fixed effects in all columns and industry fixed effects for both firms in columns 2 and 4. Notably, the coefficients on the constant term are significantly positive across all columns, consistent with our earlier findings in Table 5 that the market reacts positively to tweeted and tweeting firms around the days of positive peer tweets. Further, consistent with our expectations, the coefficients on *Future Collaboration* are significantly positive across all columns. This evidence directly links the market reactions induced by positive peer tweets to collaboration outcomes, suggesting that investors evaluate the likelihood of future inter-firm collaborations when responding to the signals conveyed through positive peer tweets .

Second, if positive peer tweets provide early signals of future collaborations between tweeting and tweeted firms, investors will be less surprised by subsequent announcements of inter-firm collaborations when these announcements were preceded by positive peer tweets. Specifically, we expect attenuated market reactions to announcements of inter-firm collaborations that are

preempted by positive peer tweets. Since the SDC Platinum provides the announcement dates of strategic alliances, we focus on strategic alliances in this analysis and construct a sample at the firm pair-strategic alliance announcement level. Our sample contains 9,450 firm pair-strategic alliance announcement observations from 2008-2023. We estimate the following regression model:

$$Ret\ alliance_{i,j,k} = \alpha + \beta_1 Peer\ Tweet\ Num_{i,j,k} + FE + \epsilon_{i,j,k} \quad (5)$$

where the independent variable of interest, *Peer Tweet Num*, is the number of positive peer tweets between firm *i* and firm *j* within the past three years before the strategic alliance announcement *k*. *Ret alliance* is the total market-adjusted CARs to announcing firm pair *i-j* on the strategic alliance announcement *k* date (measured as *[0, 0] Ret VW alliance* or *[0, 0] Ret EW alliance*). Standard errors are clustered by both firms in the firm pair.

Table 6, Panel B presents the regression results from estimating Eq. (5), using announcement-day CARs over the value-weighted (columns 1-2) or equal-weighted (columns 3-4) market portfolios as dependent variables. We include year fixed effects in all columns and further include industry fixed effects for both firms in columns 2 and 4. The coefficients on *Peer Tweet Num* are significantly negative in all four columns, ranging from -0.002 to -0.003. The results indicate that strategic alliance announcements following positive peer tweets are associated with lower announcement returns. Furthermore, the intercept is significantly positive, and the coefficients on *Peer Tweet Num* are approximately 18-30 percent of the intercept in magnitude. Together, the findings suggest that positive peer tweets reduce the positive market reactions to subsequent strategic alliance announcements, as investors have already partially incorporated the information when responding to positive peer tweets. The findings confirm that positive peer tweets provide early signals of future inter-firm collaborations and that investors anticipate subsequent strategic alliance formation between tweeting and tweeted firms.

Overall, the results in Table 6 are consistent with our prediction that investors can partially anticipate future inter-firm collaborations from the signals conveyed through positive peer tweets.

6. Additional Analyses

6.1 Spillover Effects of Future Negative News of Tweeted Firms

If positive peer tweets signal increased economic connections between two firms, and tweeting firms also benefit from sharing favorable peer information on social media, a natural question arises: Does such social signaling also impose costs on the tweeting firms? Specifically, if the tweeted firms subsequently experience unfavorable news, does the negative effect also spill over to the newly "bonded" peer firms that posted positive tweets about them, leading to negative market reactions? To test this conjecture, we focus on a specific unfavorable news event at the tweeted firm: negative management earnings forecasts. We examine market reactions to the *tweeting* firms around the tweeted firms' subsequent negative management earnings guidance by estimating Eq. (6) as below:

$$Ret\ forecast_{i,j,t} = \alpha + \beta_1 Peer\ Tweet\ Num_{i,j,t} + FE + \epsilon_{i,j,t} \quad (6)$$

The dependent variable is the three-day market-adjusted CARs to tweeting firm *i* around the management earnings guidance issued by tweeted firm *j* in quarter *t* (measured as *[-1, +1] Ret VW forecast* or *[-1, +1] Ret EW forecast*). The independent variable of interest, *Peer Tweet Num*, represents the number of positive peer tweets posted by firm *i* about firm *j* within 90 days preceding firm *j*'s management earnings guidance issued in quarter *t*. We cluster standard errors by tweeting firms when estimating Eq. (6).

To implement this test, we first obtain a sample of 20,249 negative quarterly and annual management earnings guidance issued by tweeted firms in our main sample from 2008-2023, based on I/B/E/S guidance data. An earnings guidance is classified as negative if it falls below the

mean analyst consensus forecast available at the time of the issuance of the earnings guidance (e.g., Seybert and Yang 2012). Next, using the list of all peer firm pairs constructed in Section 2, we match each negative earnings guidance from a tweeted firm with its peer firms (i.e., potential tweeting firms), constructing a sample at the peer firm-tweeted firm's negative earnings guidance level.

Table 7 reports the results. The sample comprises 440,049 potential tweeting firm-tweeted firm's negative earnings guidance level observations from 2008-2023, corresponding to 20,249 negative management earnings guidance issued by tweeted firms. In columns 1-2 (3-4), dependent variables are the three-day CARs for potential tweeting firms around their tweeted peers' negative management earnings guidance, adjusting for the value- (equal-) weighted market portfolios. We include year fixed effects in all columns and industry fixed effects in columns 2 and 4. The coefficients on *Peer Tweet Num* are negative and statistically significant across all four columns. The results suggest that when a tweeted firm issues negative earnings guidance, its peer firms that previously posted positive peer tweets about it experience lower market reactions compared to firms that didn't post positive peer tweets about the tweeted firm. The evidence indicates that tweeting positive peer news is not costless: tweeting firms experience negative market reactions when their tweeted firms subsequently experience unfavorable news.

6.2 Robustness Tests

As a robustness check, instead of focusing on the number of tone-based positive peer tweets, we use an indicator variable of tone-based positive peer tweets as an alternative measure of positive peer tweeting. We present the results of our key tests in Table A1 of the online appendix. The results are consistent with our main inferences.

Second, we use a return-based definition of positive peer tweets, as returns are comprehensive measures of information content (Kothari and Sloan 1992). We define a peer tweet as a positive peer tweet when the market-adjusted abnormal return on the tweeting day is positive. The return-based approach identifies 8,942 positive peer tweets between firm pairs with available CRSP data. We present the results of our key tests using this alternative measure in Table A2 of the online appendix. The results are in line with those obtained using the tone-based measure of positive peer tweets.

7. Conclusion

This study provides novel insights into the social dimension of social media through the lens of positive peer tweeting, where firms publicly share favorable information about their peer firms on social media. Using a sample of 6,233 positive peer tweets from 2008 to 2023, we provide the first comprehensive evidence on the determinants, information content, and capital market consequences of social signaling through positive peer tweeting.

We find that tech firms are the predominant users and targets of positive peer tweets, which occur among both vertical and horizontal peers. Firms with higher stock return correlation and common institutional blockholders are more likely to post positive tweets about each other, suggesting that economic relatedness is a contributing factor to positive peer tweeting. We also find that tweeted firms are more established than tweeting firms, and industry leaders are more likely to be the tweeted firms rather than the tweeting firms. These results indicate that tweeting firms aim to enhance their legitimacy by signaling their economic relatedness to more established and visible firms. Furthermore, positive peer tweeting is more likely to occur when tweeted and tweeting firms face higher shareholder litigation risk, suggesting that positive peer tweeting serves

as a low-risk alternative to formal disclosure channels for high litigation risk firms to signal future inter-firm collaborations.

Regarding the information content of positive peer tweets, our analyses reveal that positive peer tweets indeed provide early indications of future inter-firm collaborations. Specifically, positive peer tweets predict the formation of new inter-firm collaborations, such as becoming supply chain partners or strategic alliance partners. Further, among firms with existing collaborations, positive peer tweets predict the expansion of current collaborations. These results provide direct evidence consistent with the social signaling role of positive peer tweets.

We also examine the capital market consequences of positive peer tweets. We find that positive peer tweets generate favorable market reactions not only for tweeted firms but also for tweeting firms. The latter is particularly interesting because the positive developments and favorable news primarily pertain to the tweeted firms. We interpret the evidence as suggesting that positive peer tweets convey information about future inter-firm collaborations, which are likely to benefit the tweeting firms as well as the tweeted firms.

We conduct additional analyses to strengthen our inference that positive peer tweets provide early indications of future inter-firm collaborations. We find evidence that investor reactions to positive peer tweets vary with eventual collaboration outcomes. Specifically, investors respond more positively to tweets that are followed by the subsequent materialization of inter-firm collaborations. Additionally, consistent with positive peer tweets serving as early signals, the incidence of prior positive peer tweets reduces investors' surprise when inter-firm collaborations materialize. Specifically, positive peer tweets attenuate investor reactions to subsequent announcements of strategic alliances.

Finally, we find evidence that signaling economic ties through positive peer tweeting is not costless, as the tweeted firm's subsequent unfavorable news can spill over to the tweeting firm. Specifically, when tweeted firms release negative management earnings forecasts, firms that previously posted positive peer tweets experience negative market reactions compared to firms that did not post such tweets.

Overall, our findings suggest that social media serves as an informal yet public platform for firms to signal their connections with peers. Our evidence provides novel insights into the social dimension of social media. In doing so, we extend research on the disclosure and dissemination role of social media. Furthermore, we show that social media is a rich source of forward-looking and non-financial information not easily available through traditional disclosure channels. These findings broaden our understanding of the information role of social media and have implications for future research that further explores the unique "social" features of social media.

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Appendix A
Variable Definitions

This table provides a detailed description of the procedures used to compute each variable used in the analyses. The data are obtained through Twitter (now X), CRSP, Compustat, FactSet Revere Supply Chain Relationships, I/B/E/S, Thomson Reuters 13F, and Securities Data Company (SDC) Platinum. All continuous variables are winsorized at the 1st and 99th percentiles of their distributions.

Variables in tests of determinants (Table 3):

Variable	Definition
Peer Tweet Dummy	An indicator variable equal to one if the firm pair has at least one positive peer tweet during the year, and zero otherwise.
Stock Return Corr	Monthly stock return correlation for the firm pair during the past three years.
Common Owner	The number of common institutional blockholders shared by the firm pair during the year. We define common institutional blockholders as institutional investors concurrently holding at least 5 percent equity blocks in both firms in the firm pair.
Leader	An indicator variable equal to one if the firm is one of the top five largest firms based on sales revenues within each SIC two-digit industry-year.
Ln (Firm 2/Firm 1 Market Cap)	The natural logarithm of the ratio of the tweeted firm's market capitalization to the tweeting firm's market capitalization during the year.
Lit Risk KS	The firm-year level measure of litigation risk, based on Kim and Skinner (2012) Table 7 Model 3.
Lit Risk KY	The natural logarithm of one plus the total number of plaintiff-lawyer EDGAR views of the firm's SEC filings during the prior year. Data is from Kartapanis and Yust (2024).
Loss	An indicator variable equal to one if the firm's net income for the current year is negative, and zero otherwise.
ROA	The firm's net income for the current year scaled by total assets at the prior year-end.
MTB	The firm's market value of equity scaled by book value of equity at the prior year-end.
Sale Growth	The growth rate of the firm's sales for the current year relative to sales for the prior year.
Tweet Intensity	The number of peer tweets posted by the firm during the prior year.

Variables in tests of future product market collaborations (Table 4):

Variable	Definition
Form Relation	An indicator variable equal to one if the firm pair forms a new collaboration relationship (i.e., becomes strategic alliance partners or supply chain partners) in next three years, and zero otherwise.
Sales Percent	The average percentage of sales from the supplier firm to the customer firm in next three years.
Peer Tweet Num	The number of positive peer tweets between the firm pair during the year.
Asset Ln	The natural logarithm of the firm's total assets at the prior year-end.
Lev	The firm's long-term debt and short-term debt scaled by total assets at the prior year-end.
R&D	The firm's research and development expense for the current year scaled by total assets at the prior year-end.

Variables in tests of anticipation effect (Table 6):

Variable	Definition
[0, 0] Ret VW tweet	The summation of CARs to tweeted and tweeting firms around their positive peer tweet, adjusted by the value-weighted market portfolio.
[0, 0] Ret EW tweet	The summation of CARs to tweeted and tweeting firms around their positive peer tweet, adjusted by the equal-weighted market portfolio.
Future Collaboration	An indicator variable equal to one if the tweeting and tweeted firms form product market collaborations within three years after the positive peer tweet, and zero otherwise.
[0, 0] Ret VW alliance	The summation of CARs to tweeted and tweeting firms around their strategic alliance announcement, adjusted by the value-weighted market portfolio.

[0, 0] Ret EW alliance	The summation of CARs to tweeted and tweeting firms around their strategic alliance announcement, adjusted by the equal-weighted market portfolio.
Peer Tweet Num	The number of positive peer tweets between the firm pair within the past three years prior to its strategic alliance announcement.

Variables in tests of market reactions around unfavorable news of tweeted firms (Table 7):

Variable	**Definition**
[-1, +1] Ret VW forecast	Three-day CARs to the potential tweeting firm around the tweeted firm's management earnings guidance, adjusted by the value-weighted market portfolio.
[-1, +1] Ret EW forecast	Three-day CARs to the potential tweeting firm around the tweeted firm's management earnings guidance, adjusted by the equal-weighted market portfolio.
Peer Tweet Num	The number of positive peer tweets about the tweeted firm posted by the potential tweeting firm within 90 days prior to tweeted firm's management earnings guidance.

Appendix B
Examples of Positive Peer Tweets

This appendix lists thirteen examples of positive peer tweets in our sample, in chronological order. Column 2 lists the name of the tweeting firm, column 3 lists the name of the tweeted firm, column 4 lists the tweeting date of the positive peer tweet, and column 5 includes the tweet content along with the actual tweet link. We define a corporate tweet as a positive peer tweet if the tweeting firm expresses positive sentiment towards the tweeted firm in the tweet by including more positive words than negative words according to the financial dictionary of Loughran and McDonald (2011).

(1)	(2)	(3)	(4)	(5)
No.	Tweeting Firm	Tweeted Firm	PPT Day	Tweet Content
1	Wendy's	Coca-Cola	December 31, 2012	@SWNID @lilkup @CocaCola We like to think it means Freestyle is just that great! (tweet link: https://x.com/Wendys/status/285825376385650689)
2	Eli Lilly and Company	Pfizer Inc	April 23, 2013	@Pfizer cites an integrated, collaborative, communicative approach to #BigData analysis as a huge transformation point #BIO2013 (tweet link: https://x.com/EliLillyandCo/status/326788124061622272)
3	Cubic Corp	Northrop Grumman Corporation	November 4, 2013	Congrats @northropgrumman on a successful 1st flight of the #unmanned MQ-8C #FireScout (tweet link: https://x.com/CubicCorp/status/397389490182193152)
4	AAR Corp	Boeing Co	May 1, 2014	@Boeing 777X Clears Hurdle With FAA http://ow.ly/wnoim @aviation (tweet link: https://x.com/AARCORP/status/461903157464137729)
5	Leidos Holdings Inc	Lockheed Martin Corp	May 29, 2014	How 3D printing advanced manufacturing is redefining the production cycle at @LockheedMartin http://bit.ly/STtFeV via @TheManufacturer (tweet link: https://x.com/LeidosInc/status/471956888335417344)
6	Moog Inc	Lockheed Martin Corp	December 5, 2014	Congrats to @NASA_Orion @LockheedMartin @ulalaunch on a successful first step! Learn more about our role #OrionLaunch http://bit.ly/Moog_DeltaIVH_OrionEFT-1 (tweet link: https://x.com/Moog_Inc/status/540945274508943361)
7	Dana Inc	Ford Motor Co	March 11, 2015	The #Tonka inspired F750 from @Ford features Spicer® rear and front #axles. (Photo: Ford Motor) pic.twitter.com/MHX27rv7x3 (tweet link: https://x.com/DanaInc_/status/575680845295583235)
8	Infinity Pharmaceuticals Inc	AbbVie Inc	April 11, 2016	Congrats to @AbbVie on FDA approval of Venclexta for patients with 17 p del CLL. We're excited to have more treatment options for patients. (tweet link: https://x.com/INFIPharma/status/719631532747526144)
9	Synchronoss Technologies Inc	Qualcomm Inc	July 1, 2016	@Qualcomm Readies Lower-Band #5G testbed. Read more via @RCRWireless ubm.io/292Y9Ix (tweet link: https://x.com/Synchronoss/status/748907774696787975)

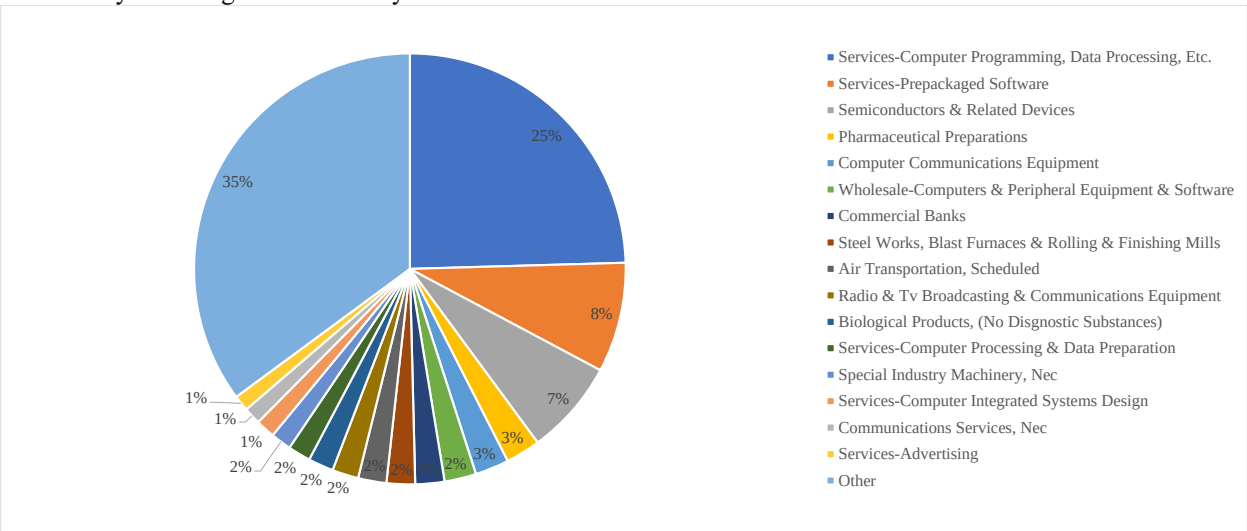
10	Mobileiron Inc	Cisco Systems Inc	September 13, 2016	5 ways Cisco might just become iPhone's best friend http://www.cio.com/article/3119589/5-ways-cisco-could-become-an-iphones-best-friend.html vi@CIOonline a .pic.twitter.com/DBgntJcL5K (tweet link: https://x.com/mobileiron/status/775789944522571776)
11	OGE Energy Corp	Gulfport Energy Corp	April 19, 2017	@GulfportEnergy benefits from energy efficiency technology. http://phx.corporate-ir.net/phoenix.zhtml?c=106374&p=irol-newsArticle&ID=2262730 (tweet link: https://x.com/OGandE/status/854782553592655873)
12	Esperion Therapeutics Inc	Merck & Co	June 27, 2017	Congrats to @Merck on positive results from their #REVEAL #CVOT for #Anacetrapib. #CETPi (tweet link: https://x.com/EsperionInc/status/879721957314396162)
13	Urban Outfitters Inc	Ralph Lauren	January 23, 2019	new Polo @RalphLauren collection featuring throwback looks inspired by the Ralph Lauren archives https://bddy.me/2R69NDb (tweet link: https://x.com/UrbanOutfitters/status/1088119214181883906)

Note to 1: Wendy's and Coca-Cola have a long-term business partnership. Coca-Cola has been the exclusive beverage supplier for Wendy's restaurants.
Note to 2: Eli Lilly and Company and Pfizer Inc are both leading companies in the pharmaceutical industry.
Note to 3: Cubic Corporation and Northrop Grumman Corporation both operate in the defense, aerospace, and technology sectors. They have collaborated on several defense projects in recent years.
Note to 4: AAR Corp and Boeing Co have maintained a business relationship through aircraft acquisitions and maintenance services.
Note to 5: Leidos Holdings Inc. and Lockheed Martin Corp are leading companies in the defense and technology sectors. They have collaborated on several defense projects in recent years.
Note to 6: Moog Inc. and Lockheed Martin Corp are both leading companies in the aerospace and defense sectors. Moog has been a key supplier to Lockheed Martin.
Note to 7: Dana Incorporated has been a supplier of Ford Motor Company.
Note to 8: Infinity Pharmaceuticals Inc and AbbVie Inc had a collaboration agreement focused on developing cancer treatments.
Note to 9: Synchronoss Technologies Inc. and Qualcomm are both leading companies in the technology sector.
Note to 10: Mobilelron Inc. and Cisco Systems have a collaborative partnership.
Note to 11: OGE Energy Corp and Gulfport Energy Corp both operate in the energy sector.
Note to 12: Esperion Therapeutics Inc and Merck & Co both operate in the pharmaceutical industry. They have a partnership focused on cholesterol-lowering treatments.
Note to 13: Urban Outfitters Inc and Ralph Lauren both operate in the fashion and retail industry. Urban Outfitters Inc. and Ralph Lauren have collaborated to offer Polo Ralph Lauren products through Urban Outfitters' retail channels in recent years.

Figure 1
Sample Distribution of Positive Peer Tweets

Panel A plots the pie chart of the sample distribution by SIC four-digit industry sectors of tweeting firms. Panel B plots the pie chart of the sample distribution by four-digit industry sectors of tweeted firms. The sample comprises 6,233 positive peer tweets from years 2008-2023.

Panel A: By Tweeting Firms' Industry Sectors



Panel B: By Tweeted Firms' Industry Sectors

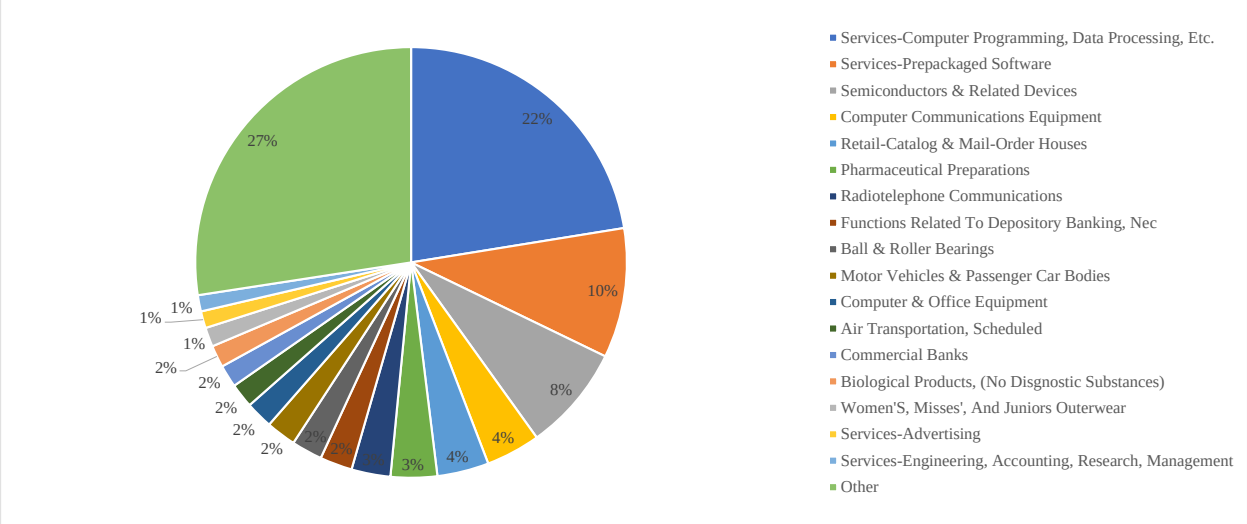


Table 1
Sample Distribution of Positive Peer Tweets

Panel A presents the top ten tweeting industries, the number of positive peer tweets associated with these industries, and the corresponding top three tweeted industries in the sample. Panel B presents the top ten tweeting and tweeted firms and the number of positive peer tweets associated with these firms. The sample comprises 6,233 positive peer tweets from years 2008-2023.

Panel A: Top Ten Tweeting Industries and the Corresponding Top Three Tweeted Industries

Rank	Tweeting SIC-4 Industry Code	Number of Positive Tweets	Tweeted SIC-4 Industry Code (Top Three)		
1	7370 Services-Computer Programming, Data Processing, Etc.	1,530	7370	7372	5961
2	7372 Services-Prepackaged Software	514	7370	7372	3674
3	3674 Semiconductors & Related Devices	444	3674	7372	7370
4	2834 Pharmaceutical Preparations	162	2834	2836	7370
5	3576 Computer Communications Equipment	158	3576	7370	3674
6	5045 Wholesale-Computers & Peripheral Equipment & Software	148	3570	7372	3576
7	6020 Commercial Banks	136	6020	6282	6141
8	3310 Steel Works, Blast Furnaces & Rolling & Finishing Mills	133	3562	3711	NA
9	4512 Air Transportation, Scheduled	132	4512	4899	4513
10	3663 Radio & TV Broadcasting & Communications Equipment	123	4812	3576	3577

Panel B: Top Ten Tweeting and Tweeted Firms

Rank	Tweeting Firm	Number of Positive Tweets	Tweeted Firm	Number of Positive Tweets
1	Channeladvisor Corp	182	Microsoft Corp	374
2	Haynes International Inc	132	Meta Platforms Inc	295
3	Cdw Corp	96	Cisco Systems Inc	232
4	Comscore Inc	74	Twitter Inc	220
5	Virtusa Corp	70	Intl Business Machines Corp	201
6	Intel Corp	60	Intel Corp	199
7	Netsol Technologies Inc	55	Timken Co	144
8	Micron Technology Inc	53	Verizon Communications Inc	142
9	Commvault Systems Inc	52	Amazon.Com Inc	137
10	Marin Software Inc	51	Adobe Inc	127

Table 2
Descriptive Statistics of Tweeting and Tweeted Firms

This table presents the descriptive statistics of tweeting and tweeted firms in the primary sample of positive peer tweets with available data for constructing the determinants. Panel A presents the descriptive statistics of tweeting firms. Panel B presents the descriptive statistics of tweeted firms. Panel C presents the pairwise comparison of tweeting and tweeted firms. All variables are defined in Appendix A. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Tweeting Firms

Variables	N	Mean	SD	P25	P50	P75
Firm 1 Asset	6,174	23,248.822	73,280.302	374.849	1,905.368	9,983.820
Firm 1 Asset Ln	6,172	7.594	2.258	5.819	7.462	9.103
Firm 1 Sales Growth	6,138	0.108	0.235	-0.006	0.071	0.180
Firm 1 Loss	6,174	0.320	0.466	0.000	0.000	1.000
Firm 1 ROA	6,172	-0.004	0.155	-0.036	0.029	0.078
Firm 1 PPE	6,142	0.162	0.182	0.048	0.092	0.191
Firm 1 Lev	6,067	0.196	0.199	0.009	0.149	0.319
Firm 1 R&D	6,172	0.082	0.098	0.000	0.053	0.126

Panel B: Tweeted Firms

Variables	N	Mean	SD	P25	P50	P75
Firm 2 Asset	6,161	80,400.949	188,641.903	3,191.172	22,659.800	105,134.000
Firm 2 Asset Ln	6,158	9.587	2.221	7.966	9.841	11.486
Firm 2 Sales Growth	6,144	0.121	0.222	-0.002	0.069	0.195
Firm 2 Loss	6,161	0.166	0.372	0.000	0.000	0.000
Firm 2 ROA	6,158	0.048	0.131	0.014	0.061	0.112
Firm 2 PPE	6,124	0.176	0.181	0.058	0.104	0.237
Firm 2 Lev	6,111	0.216	0.159	0.100	0.211	0.302
Firm 2 R&D	6,158	0.075	0.084	0.000	0.053	0.111

Panel C: Pairwise Comparison of Tweeting and Tweeted Firms

	Tweeting Firms		Tweeted Firms		
	N	Mean	N	Mean	Mean Diff
Variables	(1)	(2)	(3)	(4)	(2)-(4)
Asset	6,174	23,248.820	6,161	80,400.950	-57,152.130***
Asset Ln	6,172	7.594	6,158	9.587	-1.993***
Sales Growth	6,138	0.108	6,144	0.121	-0.013***
Loss	6,174	0.320	6,161	0.166	0.154***
ROA	6,172	-0.004	6,158	0.048	-0.052***
PPE	6,142	0.162	6,124	0.176	-0.014***
Lev	6,067	0.196	6,111	0.216	-0.020***
R&D	6,172	0.082	6,158	0.075	0.007***

Table 3
Determinants of Positive Peer Tweets

This table presents the results examining the determinants of positive peer tweets. The dependent variable, *Peer Tweet Dummy*, is an indicator variable equals to one if the firm pair has at least one positive peer tweet during the year, and zero otherwise. In column 1 (2), the sample consists of firm pair-year observations from years 2008-2023 (2008-2017). All specifications include SIC two-digit industry × year fixed effects. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm 1 and firm 2. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent variable:		*Peer Tweet Dummy*	
	Pr. Sign	(1)	(2)
Stock Return Corr	+	0.002***	0.001***
		(6.43)	(4.91)
Common Owner	+	0.001***	0.001***
		(4.67)	(3.78)
Firm 1 Leader	+	0.001***	0.001*
		(3.05)	(1.90)
Firm 2 Leader	+	0.004***	0.005***
		(3.71)	(3.40)
Ln (Firm 2/Firm 1 Market Cap)	+	0.000***	0.000***
		(3.32)	(2.79)
Firm 1 Lit Risk KS	+	0.000	
		(1.11)	
Firm 2 Lit Risk KS	+	0.000***	
		(2.80)	
Firm 1 Lit Risk KY	+		0.000**
			(2.06)
Firm 2 Lit Risk KY	+		0.001***
			(4.08)
Firm 2 Loss		-0.000***	-0.001**
		(-2.63)	(-2.28)
Firm 2 ROA		-0.001***	-0.001***
		(-3.14)	(-3.13)
Firm 1 MTB		0.000	0.000
		(1.24)	(1.08)
Firm 2 MTB		0.000	0.000*
		(1.30)	(1.73)
Firm 1 Sale Growth		0.000	0.000
		(1.22)	(0.69)
Firm 2 Sale Growth		0.000	0.000
		(0.72)	(0.77)
Firm 1 Tweet Intensity		0.001***	0.001***
		(6.30)	(5.65)
Firm 2 Tweet Intensity		0.000***	0.000***
		(3.58)	(3.20)
Firm 1 Ind × Year FE		Yes	Yes
Firm 2 Ind × Year FE		Yes	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes
No. of observations		1,532,284	931,198
Adj. R-Squared		0.010	0.012

Table 4

Information Content: Positive Peer Tweets and Future Product Market Collaborations

This table presents the results examining the association between future product market collaborations and positive peer tweeting. The sample consists of firm pair-year observations from years 2008-2023. The independent variable of interest, *Peer Tweet Num*, is the number of positive peer tweets between the firm pair during the year. Panel A presents the results examining the association between positive peer tweets and future product market collaborations. Panel B presents the results examining the association between positive peer tweets and the expansion of existing product market collaborations. In Panel A, the dependent variable, *Form Relation*, is an indicator variable equals to one if the firm pair forms a new collaboration relationship in next three years, and zero otherwise. In Panel B, the dependent variable, *Sales Percent*, is the average percentage of sales from the supplier firm to the customer firm in next three years. In each panel, columns 1-2 use the full sample of firm pairs, and columns 3-4 use the sample of firm pairs with at least one positive peer tweet during the sample period. Columns 1 and 3 includes year and firm fixed effects for both firms, and columns 2 and 4 include year and firm pair fixed effects. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by both firms. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Positive Peer Tweets and Future Product Market Collaborations

Dependent variable:		*Form Relation*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	+	0.022***	0.008***	0.016***	0.006**
		(5.28)	(2.69)	(4.12)	(2.16)
Firm 1 Asset Ln		0.001**	0.001***	0.009**	0.011***
		(2.39)	(2.85)	(2.32)	(2.83)
Firm 2 Asset Ln		0.001**	0.001***	0.009**	0.011***
		(2.39)	(2.85)	(2.32)	(2.83)
Firm 1 Sale Growth		-0.000	-0.000	0.012**	0.008
		(-0.18)	(-0.38)	(2.07)	(1.54)
Firm 2 Sale Growth		-0.000	-0.000	0.012**	0.008
		(-0.18)	(-0.38)	(2.07)	(1.54)
Firm 1 Loss		-0.001**	-0.001*	-0.012**	-0.010*
		(-2.53)	(-1.74)	(-2.05)	(-1.83)
Firm 2 Loss		-0.001**	-0.001*	-0.012**	-0.010*
		(-2.53)	(-1.74)	(-2.05)	(-1.83)
Firm 1 ROA		-0.001	-0.000	-0.050*	-0.035
		(-1.33)	(-0.68)	(-1.82)	(-1.40)
Firm 2 ROA		-0.001	-0.000	-0.050*	-0.035
		(-1.33)	(-0.68)	(-1.82)	(-1.40)
Firm 1 Lev		0.000	0.000	0.008	0.010
		(0.40)	(0.32)	(0.42)	(0.53)
Firm 2 Lev		0.000	0.000	0.008	0.010
		(0.40)	(0.32)	(0.42)	(0.53)
Firm 1 R&D		0.000	0.005***	-0.023	-0.009
		(0.12)	(3.47)	(-0.44)	(-0.18)
Firm 2 R&D		0.000	0.005***	-0.023	-0.009
		(0.12)	(3.47)	(-0.44)	(-0.18)
Sample		Full	Full	Conditional	Conditional
Year FE		Yes	Yes	Yes	Yes
Firm 1 and Firm 2 FE		Yes	No	Yes	No
Firm 1 × Firm 2 FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		1,936,078	1,930,374	58,974	58,900
Adj. R-Squared		0.049	0.359	0.156	0.337

Table 4 (continued)

Panel B: Positive Peer Tweets and the Expansion of Existing Product Market Collaborations

Dependent variable:		*Sales Percent*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	+	0.840***	0.340**	0.455***	0.350***
		(3.29)	(2.20)	(3.21)	(2.70)
Firm 1 Asset Ln		-0.671	-0.485	-0.000	-0.156
		(-0.95)	(-0.64)	(-0.00)	(-0.12)
Firm 2 Asset Ln		-0.666	-0.480	-0.000	-0.156
		(-0.95)	(-0.63)	(-0.00)	(-0.12)
Firm 1 Sale Growth		-0.656	-0.251	-0.062	0.002
		(-1.22)	(-0.66)	(-0.08)	(0.00)
Firm 2 Sale Growth		-0.664	-0.262	-0.062	0.002
		(-1.23)	(-0.69)	(-0.08)	(0.00)
Firm 1 Loss		-0.226	-0.311	-0.133	-0.269
		(-0.60)	(-1.14)	(-0.26)	(-0.53)
Firm 2 Loss		-0.226	-0.311	-0.133	-0.269
		(-0.60)	(-1.15)	(-0.26)	(-0.53)
Firm 1 ROA		0.255	-0.631	4.200	3.991
		(0.13)	(-0.44)	(1.64)	(1.54)
Firm 2 ROA		0.264	-0.618	4.206	3.995
		(0.13)	(-0.43)	(1.64)	(1.54)
Firm 1 Lev		-1.743	-2.077	-4.933	-5.413*
		(-0.86)	(-1.17)	(-1.64)	(-1.95)
Firm 2 Lev		-1.747	-2.070	-4.933	-5.412*
		(-0.87)	(-1.17)	(-1.64)	(-1.95)
Firm 1 R&D		3.758	1.781	3.245	3.209
		(0.80)	(0.40)	(0.29)	(0.30)
Firm 2 R&D		3.773	1.800	3.247	3.212
		(0.81)	(0.41)	(0.29)	(0.30)
Sample		Full	Full	Conditional	Conditional
Year FE		Yes	Yes	Yes	Yes
Firm 1 and Firm 2 FE		Yes	No	Yes	No
Firm 1 × Firm 2 FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		11,402	11,118	2,928	2,914
Adj. R-Squared		0.714	0.885	0.851	0.879

Table 5

Market Reactions to Positive Peer Tweets: Tweeted and Tweeting Firms

This table presents the results examining market reactions to tweeted and tweeting firms around positive peer tweets. The sample comprises 6,233 positive peer tweets from years 2008-2023. Panel A presents the mean market-adjusted CARs to tweeted firms around positive peer tweets. Panel B presents the mean market-adjusted CARs to tweeting firms around positive peer tweets. Panel C presents the mean market-adjusted CARs to non-tweeting peer firms around positive peer tweets, using a random sample of non-tweeting peer firms (i.e., one non-tweeting peer firm for each positive peer tweet). In each panel, column 1 (2) reports CARs adjusted by CRSP equal- (value-) weighted portfolio. CARs are multiplied by 100 for ease of interpretation. All variables are defined in Appendix A. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Market-Adjusted CARs to Tweeted Firms Around Positive Peer Tweets

	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	0.1064***	0.1036***
[0, 1]	0.1376***	0.1363***
[0, 2]	0.1719***	0.1715***
Pre-tweeting day [-1, -1]	0.0274	0.0210
No. of observations	6,233	6,233

Panel B: Market-Adjusted CARs to Tweeting Firms Around Positive Peer Tweets

	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	0.0568**	0.0523**
[0, 1]	0.1094***	0.1034***
[0, 2]	0.1886***	0.1802***
Pre-tweeting day [-1, -1]	0.0098	0.0048
No. of observations	6,233	6,233

Panel C: Falsification Test: Market-Adjusted CARs to Non-Tweeting Peer Firms Around Positive Peer Tweets

	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	0.0177	0.0115
[0, 1]	0.0556	0.0548
[0, 2]	0.0758	0.0605
Pre-tweeting day [-1, -1]	0.0415	0.0351
No. of observations	6,229	6,229

Table 6

Further Test of Signaling: Positive Peer Tweets, Anticipation Effect, and Collaboration Outcomes

This table presents the results examining the market anticipation of potential inter-firm collaborations implied by positive peer tweets. Panel A shows the results examining the future product market collaborations and total market reactions to tweeted and tweeting firms around positive peer tweets. Panel B shows the results examining positive peer tweets and future strategic alliance announcement returns. In Panel A, the sample is at the positive peer tweet level (~6,233 positive peer tweets) during years 2008-2023. The independent variable of interest, *Future Collaboration*, is an indicator variable equal to one if the tweeting and tweeted firms form product market collaborations within three years after this positive peer tweet, and zero otherwise. Dependent variables are the summation of market-adjusted CARs to tweeted and tweeting firms around positive peer tweets, including CARs adjusted by CRSP value-weighted portfolio (*[0, 0] Ret VW tweet)* and CARs adjusted by CRSP equal-weighted portfolio (*[0, 0] Ret EW tweet*). In Panel B, the sample is at the firm pair-strategic alliance announcement level (~9,450 firm pair-strategic alliance announcement observations) during years 2008-2023. The independent variable of interest, *Peer Tweet Num*, is the number of positive peer tweets for the firm pair during the past three years preceding the announced strategic alliance. Dependent variables are the summation of market-adjusted CARs to tweeted and tweeting firms around their strategic alliance announcements, including CARs adjusted by CRSP value-weighted portfolio (*[0, 0] Ret VW alliance)* and CARs adjusted by CRSP equal-weighted portfolio (*[0, 0] Ret EW alliance*). In each panel, columns 1 and 3 include year fixed effects, and columns 2 and 4 include year and SIC two-digit industry fixed effects for both firms. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by both firms. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Future Product Market Collaborations and Total Market Reactions to Tweeted and Tweeting Firms Around Positive Peer Tweets

Dependent variable:		*[0, 0] Ret VW tweet*		*[0, 0] Ret EW tweet*	
	Pr. Sign	(1)	(2)	(3)	(4)
Future Collaboration	+	0.193*	0.179*	0.195**	0.174*
		(1.95)	(1.78)	(1.96)	(1.76)
Constant		0.102*	0.108**	0.108*	0.115**
		(1.78)	(2.03)	(1.95)	(2.19)
Year FE		Yes	Yes	Yes	Yes
Firm 1 Ind and Firm 2 Ind FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		6,233	6,221	6,233	6,221
Adj. R-Squared		0.002	0.017	0.003	0.013

Panel B: Positive Peer Tweets and Future Strategic Alliance Announcement Returns

Dependent variable:		*[0, 0] Ret VW alliance*		*[0, 0] Ret EW alliance*	
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	-	-0.003**	-0.003**	-0.002**	-0.002*
		(-2.43)	(-2.02)	(-2.41)	(-1.92)
Constant		0.010***	0.010***	0.011***	0.011***
		(11.43)	(14.11)	(11.93)	(14.51)
Year FE		Yes	Yes	Yes	Yes
Firm 1 Ind and Firm 2 Ind FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		9,450	9,448	9,450	9,448
Adj. R-Squared		0.012	0.031	0.010	0.029

Table 7

Cost of Signaling: Market Reactions to *Tweeting* Firms Around Unfavorable News of Tweeted Firms (Negative Earnings Guidance)

This table presents the results examining the market reactions to tweeting firms around negative news of tweeted firms. The sample consists of potential tweeting firm-negative management earnings guidance of tweeted firm level observations from years 2008-2023. Dependent variables are the market-adjusted CARs to potential tweeting firms around their tweeted firms' negative management earnings guidance, including CARs adjusted by CRSP value-weighted portfolio (*[-1, +1] Ret VW forecast)* and CARs adjusted by CRSP equal-weighted portfolio (*[-1, +1] Ret EW forecast*). The independent variable of interest, *Peer Tweet Num*, is the number of positive peer tweets posted by the tweeting firm during the 90 days before its tweeted firm's negative management earnings guidance. Columns 1 and 3 include year fixed effects, and columns 2 and 4 include year and SIC two-digit industry fixed effects. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by tweeting firm. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent variable:		*[-1, +1] Ret VW forecast*		*[-1, +1] Ret EW forecast*	
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	-	-0.001**	-0.001***	-0.001**	-0.001**
		(-2.56)	(-2.76)	(-2.22)	(-2.36)
Constant		-0.001***	-0.001***	-0.001***	-0.001***
		(-8.22)	(-8.67)	(-6.95)	(-7.36)
Year FE		Yes	Yes	Yes	Yes
Ind FE		No	Yes	No	Yes
S.E. clustered by firm		Yes	Yes	Yes	Yes
No. of observations		440,049	440,049	440,049	440,049
Adj. R-Squared		0.001	0.002	0.001	0.002

Online Appendix for

"Beyond Disclosure: The Social Role of Social Media"

Table A1

Alternative Measure of Positive Peer Tweets: Indicator Variable of Tone-Based Positive Peer Tweets

This table presents main results using an indicator variable of tone-based positive peer tweets as a measure of positive peer tweeting. The sample consists of firm pair-year observations from years 2008-2023. The independent variable of interest, *Peer Tweet Dummy*, is an indicator variable equal to one if the firm pair has at least one positive peer tweet during the year, and zero otherwise. Panel A presents the results examining positive peer tweets and future product market collaborations. Panel B presents the results examining positive peer tweets and the expansion of existing product market collaborations. In Panel A, the dependent variable, *Form Relation*, is an indicator variable equal to one if the firm pair forms a new collaboration relationship in next three years, and zero otherwise. In Panel B, the dependent variable, *Sales Percent*, is the average percentage of sales from the supplier firm to the customer firm in next three years. In each panel, columns 1-2 use the full sample of firm pairs, and columns 3-4 use the sample of firm pairs with at least one positive peer tweet during the sample period. Columns 1 and 3 includes year and firm fixed effects for both firms, and columns 2 and 4 include year and firm pair fixed effects. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by both firms. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Positive Peer Tweets and Future Product Market Collaborations

Dependent variable:		*Form Relation*			
Definition of positve peer tweets:		LM			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Dummy	+	0.070***	0.019***	0.033***	0.009
		(8.14)	(3.60)	(4.28)	(1.63)
Controls		Yes	Yes	Yes	Yes
Sample		Full	Full	Conditional	Conditional
Year FE		Yes	Yes	Yes	Yes
Firm 1 and Firm 2 FE		Yes	No	Yes	No
Firm 1 × Firm 2 FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		1,936,078	1,930,374	58,974	58,900
Adj. R-Squared		0.049	0.359	0.155	0.337

Panel B: Positive Peer Tweets and the Expansion of Existing Product Market Collaborations

Dependent variable:		*Sales Percent*			
Definition of positve peer tweets:		LM			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Dummy	+	2.329***	0.547	0.763**	0.527*
		(3.15)	(1.32)	(2.53)	(1.71)
Controls		Yes	Yes	Yes	Yes
Sample		Full	Full	Conditional	Conditional
Year FE		Yes	Yes	Yes	Yes
Firm 1 and Firm 2 FE		Yes	No	Yes	No
Firm 1 × Firm 2 FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		11,402	11,118	2,928	2,914
Adj. R-Squared		0.714	0.885	0.851	0.878

Table A2

Alternative Measure of Positive Peer Tweets: The Number of Return-Based Positive Peer Tweets

This table presents main results using the number of return-based positive peer tweets as a measure of positive peer tweeting. Panel A presents the results examining positive peer tweets and future product market collaborations. Panel B presents the results examining positive peer tweets and the expansion of existing product market collaborations. Panel C presents the mean market-adjusted CARs to tweeted firms around positive peer tweets. Panel D presents the mean market-adjusted CARs to tweeting firms around positive peer tweets. In Panels A-B, the independent variable of interest, *Peer Tweet Num*, is the number of positive peer tweets for the firm pair during the year. In Panel A, the dependent variable, *Form Relation*, is an indicator variable equal to one if the firm pair forms a new collaboration relationship in next three years, and zero otherwise. In Panel B, the dependent variable, *Sales Percent*, is the average percentage of sales from the supplier firm to the customer firm in next three years. In Panels A-B, the sample consists of firm pair-year observations from years 2008-2023, columns 1-2 use the full sample of firm pairs, and columns 3-4 use the sample of firm pairs with at least one positive peer tweet during the sample period. Columns 1 and 3 includes year and firm fixed effects for both firms, and columns 2 and 4 include year and firm pair fixed effects. In Panels C-D, column 1 (2) reports CARs adjusted by CRSP equal- (value-) weighted portfolio. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by both firms. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Positive Peer Tweets and Future Product Market Collaborations

Dependent variable:		*Form Relation*			
Definition of positve peer tweets:		[0, 0]			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	+	0.019***	0.008***	0.013***	0.006***
		(4.62)	(3.27)	(3.96)	(2.58)
Controls		Yes	Yes	Yes	Yes
Sample		Full	Full	Conditional	Conditional
Year FE		Yes	Yes	Yes	Yes
Firm 1 and Firm 2 FE		Yes	No	Yes	No
Firm 1 × Firm 2 FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		1,936,078	1,930,374	58,974	58,900
Adj. R-Squared		0.049	0.359	0.155	0.337

Panel B: Positive Peer Tweets and Expansion of Existing Product Market Collaborations

Dependent variable:		*Sales Percent*			
Definition of positve peer tweets:		[0, 0]			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	+	0.803***	0.484***	0.655***	0.515***
		(3.09)	(3.32)	(4.30)	(3.81)
Controls		Yes	Yes	Yes	Yes
Sample		Full	Full	Conditional	Conditional
Year FE		Yes	Yes	Yes	Yes
Firm 1 and Firm 2 FE		Yes	No	Yes	No
Firm 1 × Firm 2 FE		No	Yes	No	Yes
S.E. clustered by firm 1 and firm 2		Yes	Yes	Yes	Yes
No. of observations		11,402	11,118	2,928	2,914
Adj. R-Squared		0.714	0.885	0.852	0.879

Table A2 (continued)

Panel C: Market-Adjusted CARs to Tweeted Firms Around Positive Peer Tweets

Definition of positive peer tweets:	[0, 0]	
	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	1.1976***	1.1900***
[0, 1]	1.1874***	1.1770***
[0, 2]	1.2243***	1.2093***
Pre-tweeting day [-1, -1]	0.0190	0.0098
No. of observations	8,942	8,942

Panel D: Market-Adjusted CARs to Tweeting Firms Around Positive Peer Tweets

Definition of positive peer tweets:	[0, 0]	
	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	0.2665***	0.2615***
[0, 1]	0.3330***	0.3190***
[0, 2]	0.3456***	0.3308***
Pre-tweeting day [-1, -1]	-0.0303	-0.0401*
No. of observations	8,942	8,942