Beyond Disclosure: Signaling Corporate Ties on Social Media

Abstract

This study provides the first systematic evidence on the "social" (relational) dimension of social media. We present novel evidence that firms use peer tweets to signal economic ties with other firms. By analyzing firms that actively follow and share the developments of their peers on social media, we shed light on the following: the characteristics of firms engaging in corporate social signaling, whether such signals predict future strengthened economic ties, and how investors perceive such tweets. We find that peer tweeting is associated with economic relatedness, the demand for legitimacy, and litigation risk. These tweets predict future inter-firm collaborations, conveying information not readily available through traditional disclosure channels. Furthermore, peer tweets generate significantly positive market reactions for both the tweeting and tweeted firms. However, this corporate social signaling also has a downside: tweeting firms experience negative market reactions when the firms they have tweeted about subsequently release negative news. These findings highlight social media's social dimension 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; Crowley et al. 2024, 2025). While the literature has extensively studied social media's "media" dimension, i.e., information disclosure and dissemination, the "social" dimension (i.e., the relational aspect) remains largely unexplored. The social dimension is central to individuals' social media activity. As Boyd and Ellison (2007) note, the ability of individuals to articulate their social connections and make them publicly visible is a key distinguishing feature of social media. In this study, we investigate whether firms similarly employ social media to signal economic ties with other firms, referred to hereafter as *corporate social signaling*, and whether such signals provide useful information for investors.

Unlike private channels, the public nature of social media offers a unique platform for firms to signal their economic connections with other firms. One way to signal such connections is by demonstrating ongoing interest in other firms on social media platforms, for example, by actively following their developments or frequently mentioning them. Using a novel sample of firms that post information about their peers on social media, we aim to provide the first systematic evidence on corporate social signaling. Specifically, we examine the characteristics of firms engaging in

corporate social signaling, explore whether such signals predict future strengthened economic ties, and analyze the related capital market consequences.[1]

To capture corporate social signaling, we focus on firms that engage in "peer tweeting," i.e., sharing information related to their peers on Twitter (now X). For example, on July 1, 2016, Synchronoss Technologies Inc. (SNCR) tweeted: "@Qualcomm Readies Lower-Band #5G testbed." This tweet illustrates the defining features of peer tweets in our study: (1) it mentions a new development at the *tweeted* firm (Qualcomm) but not for the tweeting firm (Synchronoss); (2) the information is related to a technological development, i.e., non-financial; and (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 peer tweets in our sample.

We posit that peer tweets may serve as early signals of firms' economic ties, particularly when future collaboration is uncertain and formal announcements, such as through press releases and earnings conference calls, are premature due to potential regulatory or legal concerns. Compared to formal announcements, social media signals are flexible and more timely.[2] However, such informal signals may lack credibility. For example, firms might post peer tweets about industry leaders to imply connections even when no strong current or future ties exist. Ultimately, it remains an empirical question whether peer tweets serve as effective signals, that is, whether they predict stronger inter-firm connections and whether investors respond to such signals.

[1] Corporate following of other corporations on Twitter can also signal interest in these firms and potential connections. However, historical following or unfollowing activity is not available, and only the current following list is observable. The static nature of this current corporate following further limits its usefulness for empirical analyses. Peer tweets, in contrast, offer dynamic signals of ongoing interest in other firms and potential connections.

[2] Corporate press releases are typically self-disclosures. While firms can mention peer firms during earnings conference calls (Brochet et al. 2018), these calls typically occur quarterly, whereas firms tweet on average five times a week (see https://get.rivaliq.com/hubfs/eBooks/Rival-IQ-2022-Social-Media-Industry-Benchmark-Report.pdf). Furthermore, these earnings call discussions typically involve rival firms, for example, an analyst asking about Coke on a PepsiCo conference call and vice versa.

To obtain a sample of peer tweets, we follow three steps. First, we construct pairs of potentially economically related peer firms based on their product market relatedness (e.g., Baiman and Rajan 2002; Schloetzer 2012; Arya et al. 2019). Because inter-firm economic links can arise from both horizontal relationships in product markets and vertical relationships along supply chains, we consider both same-industry (horizontal) and supply-chain (vertical) relationships when forming firm pairs. Second, we search for peer tweets between these firm pairs from January 1, 2008, to December 31, 2023. Finally, we exclude negative peer tweets, as they are (1) uncommon,[3] and (2) likely driven by other considerations, such as the desire to damage rivals' competitive positions (Cao et al. 2021). Our sampling procedure yields a sample of 18,295 non-negative peer tweets with available data.

Our empirical analysis begins by examining the characteristics of firms that post 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. Peer tweets occur between horizontal industry peers and vertical supply chain peers. Notably, the firms being tweeted about tend to be more established (e.g., Microsoft and Intel).

We conjecture that peer tweets are more likely to occur among firms with common ties and whose fortunes tend to move together. Indeed, we find that firms sharing common blockholders and exhibiting higher stock return correlations are more likely to post peer tweets. While industry leaders frequently initiate and receive tweets, they are four to five times more likely to receive such tweets than to initiate them. Larger firms are also more likely to be the subjects of peer tweets. These results suggest that tweeting firms are motivated to enhance their legitimacy and status by signaling economic ties with prominent and highly visible firms. Finally, given the high

[3] Negative peer tweets are uncommon and represent only 2% of the total peer tweets.

shareholder litigation risk associated with formal firm disclosures (Rogers et al. 2011; Cazier et al. 2024), 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 peer tweets is positively associated with the litigation risk of both the tweeted and tweeting firms. Overall, our evidence suggests that peer tweets are associated with inter-firm relatedness, product market power, and litigation risk.

Our second analysis centers on the *information content* of peer tweets, specifically whether they predict stronger future economic ties between the tweeting and tweeted firms, compared to non-tweeting peers. Indeed, after controlling for firm characteristics and firm pair and year fixed effects, we find strong evidence that the frequency of peer tweets is positively associated with the likelihood of the two firms becoming strategic alliance partners or supply chain partners within the next three years. In terms of economic magnitude, a one-standard-deviation increase in the number of peer tweets for a given firm-pair-year translates to a 7.1-21.3% increase in the likelihood of forming a new collaborative relationship within three years (relative to the unconditional mean). These results suggest that peer tweets can serve as a valuable signal that incrementally predicts future inter-firm collaborations.

In addition to forming new relationships, firms with existing partnerships may expand their collaborations. We hypothesize that peer tweets between firms can signal future expansion of their current relationships. Using a sample of supplier-customer firm pairs with available inter-firm sales data, we find that the number of peer tweets is positively associated with increased future sales between the two firms. Specifically, the higher the frequency of 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 peer tweets signal not only new collaborations among firms but also the expansion of existing collaborations.

After documenting that peer tweets signal future economic collaborations, our next set of analyses examines how investors perceive and react to peer tweets. Specifically, do investors perceive peer tweets as indicating a higher likelihood of future inter-firm collaborations and respond positively? We examine the market reactions to peer tweets for both tweeted and tweeting firms. We find that a tweeted firm, on average, experiences a positive market-adjusted cumulative abnormal return (CAR) of 8-9 basis points (0.08-0.09%) on the tweeting day, 12-13 basis points over the [0, 1] two-day window, and 15-17 basis points over the [0, 2] three-day window.[4] The positive market reaction is consistent with investors revising upward their assessment of the probability of a future inter-firm collaboration. It is also possible, though, that for a tweeted firm, the positive market reaction is partly due to the new development at the tweeted firm (as featured in the peer tweet) being more broadly disseminated.

Interestingly, we also find a positive reaction for the *tweeting* firm on the peer tweet day, with an average CAR of 8 basis points. The CAR increases to 9-10 basis points over the [0, 1] two-day and the [0, 2] three-day windows.[5] Notably, this reaction occurs despite the tweeting firm posting content not directly related to its own operations. While the market reaction for the *tweeted firm* could be confounded, the inference about the market reaction for the *tweeting firm* is relatively clean. Collectively, these findings are consistent with investors viewing peer tweets as signals of a future partnership that creates value for both the tweeted and the tweeting firm.

[4] For a tweeted firm with the average market capitalization in our sample (~$89,367.324 million) in our sample, the three-day CAR corresponds to an increase in firm value of $138-149 million.
[5] For a tweeting firm with the average market capitalization in our sample (~$14,231.261 million), the three-day CAR corresponds to an increase in firm value of $13-15 million.

To strengthen our inference regarding the signaling role of peer tweets, we conduct several additional analyses. First, we perform a falsification test to confirm that positive market returns accrue specifically to firms that engage in 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 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 peer tweets.

Next, we examine whether the market reactions to peer tweets are indeed related to the likelihood of future inter-firm collaborations (strategic alliance or supply chain relationship). We start by examining whether investor reactions to peer tweets vary with subsequent collaboration outcomes. If the market reaction to peer tweets is driven by investors' assessment of the likelihood of a future collaboration, it should be higher when collaborations appear more likely (e.g., those that eventually materialize). Indeed, we find that investors react more positively to peer tweets followed by subsequent inter-firm collaborations, directly linking investor reaction to collaboration outcomes. This evidence also suggests that, on average, investors can distinguish peer tweets that are cheap talk from those that are credible signals.

In a follow-up test, we focus on the subsample of strategic alliances, where we can identify the announcement dates, and analyze investors' reactions to the *announcements* of strategic alliances in relation to peer tweets. If investors view peer tweets as credible signals of future strategic alliances and impound that information, the anticipation effect should reduce the surprise and attenuate the market reactions to the actual alliance announcements. Our analysis of CARs confirms this interpretation: prior peer tweets dampen the positive market reactions to subsequent

alliance announcements. This finding provides further evidence consistent with the signaling role of peer tweets.

The evidence that positive abnormal returns accrue to firms posting peer tweets raises the question: do tweeting firms face any downside by posting peer tweets? In particular, if tweeted firms subsequently experience negative developments, does the negative news from tweeted firms spill over to tweeting firms that have now signaled strong economic connections? To shed light on this question, we focus on an adverse event for tweeted firms: negative management earnings guidance. Specifically, we examine the market reactions to *tweeting* firms around the tweeted firm's subsequent negative earnings guidance. Interestingly, the evidence shows that when a tweeted firm issues negative earnings guidance, peer firms that posted tweets about it experience lower CARs than those that did not. This result illustrates the trade-offs for firms signaling economic ties via peer tweets: while such signals can lead to positive reactions, a downside is that tweeting firms can suffer negative spillovers when the tweeted firm experiences negative news.

In additional analyses, we explore an alternative measure of future economic ties beyond strategic alliances and supply chain relationships. Specifically, firms with stronger economic ties are likely to be increasingly exposed to common shocks and therefore exhibit greater stock return co-movement. We compare the return co-movement between a tweeting firm and its tweeted peer before and after a peer tweet. We find that return co-movement increases significantly following peer tweets, confirming earlier evidence that peer tweets signal stronger future economic ties.

While our study provides evidence suggesting that peer tweets predict strengthened future economic connections, we cannot distinguish between two scenarios: (1) peer tweets merely reflect strengthened connections (because economic ties naturally create interest in the connected firms), or (2) peer tweets attract attention from the tweeted firms, creating opportunities for collaborations.

Regardless, peer tweets, as early signals of inter-firm collaborations, shed light on the "relational" aspect of social media.

We contribute to multiple strands of literature. Our most important contribution is to provide the first systematic evidence on the "social" dimension of social media, which goes beyond the well-studied "media" dimension (see, e.g., Blankespoor et al. 2014; Lee et al. 2015; Miller and Skinner 2015; Jung et al. 2018; Al Guindy et al. 2024; Crowley et al. 2024, 2025; Marshall et al. 2025). Social signaling can serve as an early indicator of firms' economic ties, while circumventing potential regulatory or legal complexities associated with formal disclosures. 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, such as inter-firm collaborations. Because such information is not readily available through other disclosure channels, it can be valuable to investors by lowering their information acquisition and processing costs (Blankespoor 2019; Blankespoor et al. 2020; deHaan et al. 2023). Our findings extend prior literature that documents social media's role in disclosing financial information, such as earnings and sales (e.g., Blankespoor et al. 2014; Bartov et al. 2018; Tang 2018; Cookson et al. 2024; deHaan et al. 2026).

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). Whereas previous studies have focused on negative peer disclosures, we examine general (non-negative) peer disclosures, which are empirically distinct and driven by different economic forces. Negative peer disclosures are motivated by firms' desire to harm rivals' competitive positions (Kim et al.

2020; Cao et al. 2021; Bloomfield et al. 2024). In contrast, general peer tweets can 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 peer tweets used in our primary analyses. First, we construct a set of potentially connected peer firm pairs (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, 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 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 for tweets posted by firm *i* (*j*) that mention firm *j* (*i*). To

ensure the tweets are non-trivial, we require all tweets to include a hyperlink to external news sources.[6] This step yields 32,419 peer tweets posted between 5,488 firm pairs.

Third, we exclude negative peer tweets, as negative tweets reflect an intent to harm a peer firm's strategic position rather than a desire to signal connections (Cao et al. 2021). A peer tweet is classified as negative if the tweet contains more negative than positive words, as defined by Loughran and McDonald (2011). Using this tone-based approach, we classify 31,726 peer tweets as non-negative.[7] After excluding tweets from firms in the financial industries (i.e., SIC codes 6000-6999) or those with missing CRSP return information, our sample consists of 18,295 non-negative peer tweets from 2008-2023.[8] Appendix B presents examples of non-negative 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, technology firms (e.g., computer, software, semiconductor, etc.) are the most frequent posters and receivers of 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 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

[6] The hyperlink requirement also ensures that the tweeting firm is not breaking new information, allowing us to sharpen the focus on the social signaling role of the tweets. For example, the Synchronoss tweet referenced earlier contains a link to an article in *Light Reading*, a telecom industry newsletter. It was published on June 26, 2016, several days before the tweet on July 1st.

[7] Negative peer tweets represent only 2% (693 out of a total of 32,419) of the total peer tweets.

[8] We exclude 2,026 tweets involving media companies (e.g., TheStreet, Inc.) as either the tweeting or tweeted firm, as such tweets are part of their core business activities rather than online socializing efforts.

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 ($13,088 vs. $60,408 million) and less profitable, as measured by both loss occurrence and return on assets (0.351 vs. 0.169; -0.010 vs. 0.049). 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 Peer Tweets

In this section, we explore factors that influence the tendency to engage in peer tweeting. Specifically, we examine three sets of firm characteristics likely associated with peer tweets: (1) the economic closeness of the firms, (2) product market power dynamics, and (3) litigation risk.

First, the closeness between the two firms in the product and capital markets can influence a firm's tendency to post 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 peer tweeting. However, it is also possible that these firms are less likely to post peer tweets because the peer firms may be competitors. To capture the economic relatedness 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).[9] We posit that a firm pair whose fortunes move together has a greater potential for

[9] 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.

mutually beneficial collaborations, increasing the likelihood of 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 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 peer tweets to signal their close ties with industry leaders. At the same time, industry leaders might also use 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 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 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, 1997; Field et al. 2005). Since shareholder litigation often targets formal

corporate disclosures (Rogers et al. 2011; Cazier et al. 2024), firms facing high litigation risk tend to exercise greater caution when disclosing uncertain information through formal channels. If either the tweeting firm or the tweeted firm faces high litigation risk and refrains from formal disclosures, peer tweets may serve as a low-risk alternative for firms to provide early signals of potential future collaborations without directly increasing either party's legal exposure. Thus, we expect the likelihood of peer tweets to increase if either the tweeting firm or the tweeted firm faces high litigation risk. We measure firms' shareholder litigation risk using two approaches: (1) the litigation risk model in Kim and Skinner (2012, Table 7, Model 3) (*Lit Risk KS*), consistent with prior studies such as Cao and Narayanamoorthy (2014) and Donelson et al. (2022); and (2) 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).

To examine the determinants of 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. 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 non-negative 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 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 (smaller sample size due to the data availability). The inferences are similar across both columns. Firm pairs with more positive stock return correlations and common blockholders are more likely to engage in peer tweeting, as these firms are closely related and have more potential collaborative opportunities.

We also find that industry leaders are prominent as both tweeting and tweeted firms. Notably, the probability of industry leaders being mentioned in peer tweets is four to five times higher than the likelihood of industry leaders tweeting about other firms.[10] 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 peer tweets. The findings are consistent with tweeting firms enhancing their legitimacy by signaling their economic relatedness to more successful firms.

Moreover, consistent with expectations, the likelihood of peer tweets increases when either the tweeted firm or the tweeting firm faces high litigation risk. Specifically, the coefficient on the litigation risk of firm 2 (i.e., the tweeted firm) is positive and significant across both measures of litigation risk, and the coefficient on the litigation risk of firm 1 is positive and significant using the second litigation risk measure (column 2). The evidence suggests that peer tweets may serve as a low-risk signal of future inter-firm collaborations when litigation concerns deter firms from formal disclosures.[11]

[10] In column 1, the coefficient on *Firm 2 Leader* is 0.010, and the coefficient on *Firm 1 Leader* is 0.002, so the relative increase in likelihood is 0.010/0.002 - 1 = 4.

[11] While the tweets are initiated by the tweeting firms, the absence of formal disclosures by the tweeted firms (due to litigation concerns) can also prompt the tweeting firms to use peer tweets as a signaling tool.

Although not formally hypothesized, we also examine the effect of financial performance, as it is plausible that firms post peer tweets to maintain and signal good relationships with well-performing firms. 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 peer tweets, suggesting a positive association between firm performance and being the subject of peer tweets. However, firms with high ROAs are less likely to receive peer tweets, contradicting the earlier evidence.

In addition to the above factors, we control for both the tweeting and tweeted firms' market-to-book ratio (*MTB*) and sales growth rate (*Sale Growth*). We also control for a firm's social media engagement tendency, i.e., how frequently it mentions other firms on social media. We construct a variable, *Tweet Intensity*, which is the total volume of peer-related tweets posted by the firm, measured over the previous year. Not surprisingly, peer tweets are more likely when either the tweeting firm or the tweeted firm actively engages in peer-related social media activity.

4. Peer Tweets and Future Collaborations (Information Content)

In this section, we explicitly examine the information content of 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 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.[12] The second sample (conditional sample) includes 57,486 firm-pair-year observations of firm pairs that have posted at least one peer tweet during the entire sample period. We estimate a linear probability model using Eq. (2) as follows:

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

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*).[13] 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 (non-negative) peer tweets between firm *i* and firm *j* in year *t*, posted by either firm *i* or firm *j*.[14] *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.

[12] The sample size is larger than the sample in Table 3 because of the data availability of control variables.
[13] 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.
[14] In the full sample, *Peer Tweet Num* has a mean of 0.013, a standard deviation of 0.425, and ranges from 0 to 133, with 133 being the 99th percentile. In the conditional sample, *Peer Tweet Num* has a mean of 0.426 and a standard deviation of 2.430.

The coefficients on *Peer Tweet Num* are consistently positive and statistically significant across all specifications, suggesting that peer tweets signal future partnerships, including 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 21.3% increase in the likelihood of forming a new collaborative relationship within the next three years (relative to the unconditional mean).[15] 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 a 7.1% relative increase in the probability of forming a new collaboration. The results for the conditional sample, consisting of firms that have posted at least one 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 *Peer Tweet Num* is comparable to those estimated in columns 1-2: 18.4% in column 3 and 7.4% in column 4. These findings highlight that peer tweets can predict the formation of inter-firm collaborations.[16]

The above analysis focuses on the formation of new collaborations. Next, we investigate the signaling role of peer tweets for firms with existing collaborations. We hypothesize that peer tweets between collaborating firms indicate the potential expansion of their existing collaborations. To test this prediction, we focus on a subsample of supplier-customer pairs with available inter-firm sales data, which allows us to quantify the scope of collaborations between firms along the

[15] The mean value of *Form Relation* is 0.012. The standard deviation of *Peer Tweet Num* is 0.425. Thus, the economic magnitude is $0.006 \times 0.425 \div 0.012 = 21.3\%$.

[16] By posting peer tweets, firms may not only signal current and future connections but also strengthen ties with potential collaborators. In this study, we do not distinguish between the two cases: signaling or strengthening connections. In either case, peer tweets can serve as early signals of inter-firm connections.

supply chain.[17] 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 peer tweets between this firm pair *i-j* in year *t*, as shown in Eq. (3). We employ an unconditional sample consisting of 10,770 firm-pair-year observations for customer-supplier pairs, and a conditional sample consisting of 2,676 firm-pair-year observations of firm pairs that have posted at least one peer tweet during our sample period.

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

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 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* (~2.028) is associated with an increase in inter-firm sales of 0.436 percentage point, equivalent to 2.4% of the mean of *Sales Percent*. Overall, peer tweets signal not only future collaborations among firms without existing collaborations but also the future expansion of collaborations among firms with established relationships.

5. Capital Market Consequences of Peer Tweets

[17] In this test, we do not include strategic alliances as there is no available data to measure the extent of collaboration within existing strategic alliances.

The previous analyses provide evidence that peer tweets signal strengthened future inter-firm connections. In this section, we examine the capital market consequences of 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 peer tweets occur. Table 5, Panel A reports the mean market-adjusted CARs for tweeted firms around the days of peer tweets. The results suggest that, on average, a tweeted firm experiences an abnormal return of 9 basis points (0.09 percent) over the equal-weighted market portfolio and 8 basis points over the value-weighted market portfolio on the day of the tweet. The two-day and three-day CARs, measured from the tweeting day, increase to 12-13 basis points and 15-17 basis points, respectively. We cluster standard errors by tweeting date to account for cross-sectional correlation across firms on the same trading day (e.g., Liu et al. 2023; Fang et al. 2025). All of these CARs are statistically significant at the 1% or 5% level. For a tweeted firm with the average market capitalization in our sample (~$89,367 million), the three-day CAR corresponds to an increase in firm value of $149 million.[18] Peer tweets likely generate positive market reactions for tweeted firms for several reasons. First, peer tweets can signal potential future inter-firm collaborations that create value for both firms. Additionally, the peer tweets, through sharing new development at the tweeted firm, likely increase awareness of such information.

Although the new development primarily pertains to the tweeted firm, investors may react positively to the tweeting firm if peer tweets signal future inter-firm collaborations. Table 5, Panel B reports the mean market-adjusted CARs for tweeting firms around the days of peer tweets.

[18] Based on column 1 in Table 5, Panel A, for a tweeted firm of average market capitalization (~$89,367.324 million), the increase in firm value is calculated as $89,367.324 million × 0.1670% = $149 million.

Interestingly, tweeting firms also experience positive abnormal returns around the tweeting days. They experience an average CAR on the tweeting day of 8 basis points over the equal- or value-weighted market portfolios, and an average CAR of 9-10 basis points (0.09-0.10 percent) over the two-day window [0, 1] and the three-day window [0, 2]. For a tweeting firm with the average market capitalization in our sample (~$14,231 million), the three-day CAR corresponds to an increase in firm value of $13-15 million.[19] In contrast, the CARs on day [-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 signal sent by the tweeting firm, likely because they interpret it as an indication of a higher likelihood of future inter-firm collaborations that create value for both firms.

We interpret the positive abnormal returns for both tweeted and tweeting firms as evidence that investors react to the social signals associated with peer tweeting. However, a potential concern is that *all* peer firms, and not just firms posting peer tweets, experience positive market reactions because tweeted firms' new developments may spill over to all peer firms. We conduct a falsification test by examining the market reactions to *non-tweeting* peer firms around the days of peer tweets. Specifically, for each tweeting firm, we use propensity score matching (PSM) to identify a similar non-tweeting firm from the tweeted firm's peers. The matching procedure employs all control covariates used in Eq. (2), including firm size, sales growth, loss, ROA, leverage, and R&D intensity. Table 5, Panel C presents the results for non-tweeting peer firms.

In contrast to the evidence for the tweeting peer firms, the results in Table 5, Panel C suggest that PSM-matched non-tweeting peer firms do not experience significant market reactions

[19] Based on column 1 in Table 5, Panel B, for a tweeting firm of average market capitalization (~$14,231.261 million), the increase in firm value is calculated as $14,231.261 million × 0.1042% = $15 million.

around the tweeting days, and the magnitude of the market reaction is substantially muted compared to that of the tweeting firms.

To highlight the incremental signaling value of peer tweeting, we perform an additional analysis in Panel D, where we compare the market reactions of tweeting firms and PSM-matched non-tweeting peer firms using a regression framework. Specifically, for each tweet, we include the tweeting firm and its PSM-matched non-tweeting peer firm. We present the results for the event window [0, 0], but our results are consistent if we use the event window [0, 1] or [0, 2]. After controlling for year and tweet fixed effects, we find consistent evidence that tweeting firms experience significantly more positive market reactions on the tweeting day, relative to non-tweeting peers. Consistent with the evidence in Panel C, non-tweeting peer firms, as indicated by the constant term, exhibit no significant market reactions. Taken together, this evidence mitigates the concern that the observed positive stock market reactions 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 peer tweets.

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

So far, we have demonstrated that peer tweets signal increased future inter-firm collaborations, and that investors respond positively to these signals for both the tweeting and tweeted firms. To strengthen our inference that investors' reaction to peer tweets is primarily driven by their assessment of an increased likelihood of future inter-firm collaborations, we conduct two additional analyses to directly examine the anticipatory effects of peer tweets.

First, we examine whether the market reactions to peer tweets vary with subsequent collaboration outcomes. If the market reaction to peer tweets is driven by investors' assessment of

the likelihood of a future inter-firm collaboration, it should be stronger for cases where collaborations appear more likely (e.g., those that eventually materialize). To test this conjecture, we use our main sample of 18,295 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 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 peer tweet *x*, and zero otherwise. The three-year time window is consistent with the time frame in the tests of future inter-firm 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 the [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 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 the market reaction tests in previous sections, we cluster standard errors by tweeting date.

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 further include year and both firms' industry fixed effects in columns 2 and 4. Consistent with our expectations, the coefficients on *Future Collaboration* are significantly positive across all columns and roughly two to three times the magnitude of the intercept. This evidence directly links the market reactions induced by peer tweets to collaboration outcomes, suggesting that investors evaluate the likelihood of future inter-firm collaborations when

responding to the signals conveyed through peer tweets and that they can largely differentiate tweets that are cheap talk from those that are credible signals.

Second, we focus on the subsample of strategic alliances, where we can identify the announcement dates, and analyze investors' reactions to the strategic alliance *announcements* in relation to prior peer tweets. If investors view peer tweets as credible early signals of future strategic alliances and impound that information, they will be less surprised by the actual alliance announcements. Specifically, we expect attenuated market reactions to strategic alliance announcements preceded by 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 to 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 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 strategic alliance announcement date.

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 and both firms' industry fixed effects in columns 2 and 4. The coefficients on *Peer Tweet Num* are significantly negative in all four columns, ranging from -0.085 to -0.133. The results indicate that strategic alliance announcements

following peer tweets elicit lower announcement returns. The intercept is significantly positive, suggesting that on average, the market reacts positively to strategic alliance announcements. Together, the findings suggest that peer tweets reduce the positive market reactions to subsequent strategic alliance announcements, as investors have already partially incorporated that information when responding to peer tweets.

Overall, the results in Table 6 are consistent with our inference that peer tweets provide early signals of future inter-firm collaborations.

6. Spillover Effects of Future Negative News of Tweeted Firms

If peer tweets signal increased economic connections between two firms and the tweeting firm experiences a positive market reaction, a natural question arises: Does this social signaling also have a downside for tweeting firms? If not, other firms can mimic this strategy, undermining the value of peer tweets as a credible signal. We hypothesize a potential downside of peer tweets: a negative spillover effect from the tweeted firm. Specifically, we examine whether subsequent unfavorable news about the tweeted firm spills over and leads to a negative market reaction for the tweeting firm.

To test this conjecture, we focus on a specific unfavorable news event: negative management earnings forecasts. We examine the market reactions to *tweeting* firms when tweeted firms subsequently release negative earnings forecasts. We estimate Eq. (6) as follows:

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

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 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 management earnings guidance issuance date when estimating Eq. (6).

To implement this test, we first obtain a sample of 4,709 negative quarterly and annual management earnings guidance issued by tweeted firms in our main sample from 2008 to 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 earlier, we match each negative earnings guidance from a tweeted firm with all its peer firms, regardless of prior peer tweets, resulting in a sample at the peer firm-tweeted firm's negative earnings guidance level.

Table 7 reports the results. The sample comprises 442,757 potential tweeting firm-tweeted firm's negative earnings guidance level observations from 2008-2023, corresponding to 4,709 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 and potential tweeting firms' 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 peer tweets about it experience more negative market reactions compared to peers that did not engage in peer tweeting. This evidence highlights the trade-offs for firms engaging in peer tweets: while such signals can lead to positive reactions, a downside is that a tweeting firm can suffer negative spillovers when the tweeted firm experiences bad news.

7. Additional Analysis

7.1 Positive and Neutral Peer Tweets

Our primary analysis has focused on non-negative peer tweets without distinguishing between positive and neutral tweets. We conjecture that demonstrated interest in another firm can, by itself, signal potential inter-firm collaborations. Furthermore, the character limit of tweets means that traditional sentiment classification likely contains significant measurement errors. Nevertheless, in this section we classify peer tweets into positive and neutral tones and examine whether the signaling strength differs.

We classify our sample of non-negative peer tweets into positive (n=5,478) and neutral (n=12,817) categories. Table 8 reports the mean CARs for tweeted (Panel A) and tweeting (Panel B) firms around the days of peer tweets. The results suggest that both experience positive market reactions, regardless of the tone of the tweets. Importantly, for both the tweeted and the tweeting firms, the market reactions do not differ significantly between positive and neutral tones.

7.2. Signaling Value of Peer Tweets: Socially Active vs. Inactive Firms

We explore whether investors react differently to peer tweets posted by "socially active" firms, which frequently tweet about peer firms, versus those that rarely do so. On the one hand, peer tweets from *socially inactive* firms may send a stronger signal to investors and elicit greater market reactions, because these tweets seem more purposeful. On the other hand, socially active firms are experienced in signaling via social media, and investors may find these signals more credible. In Table 9, we compare the market reaction to peer tweets for the two types of firms. We split the sample into two subsamples based on whether the tweeting firm has a higher tweeting intensity than the sample median in the previous year. The results suggest that, for both the tweeted firm and the tweeting firm, the market reactions to peer tweets by socially inactive firms are significantly higher than those from active firms, likely due to the high salience of these tweets.

7.3. Alternative Measure of Economic Ties

In this section, we explore an alternative measure of strengthened economic ties other than the formation of strategic alliances or supply chain relationships. Specifically, firms with stronger economic ties are likely to be increasingly exposed to common shocks and therefore exhibit greater stock return co-movement. We therefore test the prediction that firm pairs involved in peer tweets exhibit greater stock return co-movement following the tweet.

Following prior literature (e.g., Dyer et al. 2024), we measure stock return co-movement (*Return Comovement*) as the Pearson correlation coefficient between daily stock returns of the two firms in a firm pair over a 90-day window. For each peer tweet, we construct two firm-pair observations: a pre-tweet observation based on stock return co-movement over days [-90, -1] and a post-tweet observation based on stock return co-movement over days [1, 90]. The main independent variable, *After Peer Tweet*, is an indicator equal to one for post-tweet observations and zero for pre-tweet observations. The dependent variable, *Return Comovement*, is measured as the Pearson correlation between the daily stock returns of the two firms in the pair over the corresponding 90-day window.

We construct two samples. For the first sample, we exclude peer tweets that are preceded by another peer tweet involving the same firm pair within the previous 90 days to ensure clean identification of pre- and post-tweet return windows. This restriction also prevents overlap in event windows for a given firm pair. We also construct a more restrictive sample, which retains only the first peer tweet observed for each firm pair during the sample period.

Table 10 presents regression evidence on the relation between peer tweets and pairwise stock return co-movement. Columns 1-2 are estimated using the first sample, whereas columns 3-4 are estimated using the more restrictive sample. Columns 1 and 3 include year fixed effects, and columns 2 and 4 include both year and firm pair fixed effects. Across all specifications, the

coefficient on *After Peer Tweet* is significantly positive, suggesting that stock returns of the two firms move more closely together following a peer tweet. This evidence confirms the earlier inference that peer tweets signal stronger future economic ties.

7.4 Other Robustness Checks

As a robustness check, we use an indicator variable (instead of the number of peer tweets) to measure peer tweeting. We rerun the analysis in Table 4 (predicting future collaboration) using this alternative measure and present the results in Table OA1 of the online appendix. The results are consistent with our main inferences.

Second, we use a return-based measure of non-negative peer tweets, as returns are comprehensive measures of information content (Kothari and Sloan 1992). We define a peer tweet as non-negative when the market-adjusted abnormal return for the tweeted firm on the tweeting day is non-negative. This approach identifies 8,942 non-negative peer tweets between firm pairs with available CRSP data. We rerun the analysis in Table 4 (predicting future collaboration) using this alternative measure and present the results in Table OA2 of the online appendix. The results are consistent with those obtained using the tone-based measure of non-negative peer tweets.

8. Conclusion

This study provides novel insights into the social (relational) dimension of social media through the lens of peer tweeting, where firms publicly share information about their peer firms on social media. Using a sample of 18,295 non-negative 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 peer tweeting.

We find that technology firms are the predominant users and targets of 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 tweets about each other, suggesting that economic relatedness is a contributing factor to 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, peer tweeting is more likely to occur when tweeted and tweeting firms face higher shareholder litigation risk, suggesting that 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 peer tweets, our analyses reveal that peer tweets indeed provide early indications of future inter-firm collaborations. Specifically, peer tweets predict the formation of new inter-firm collaborations, such as becoming strategic alliance partners or supply chain partners. Further, among firms with existing collaborations, peer tweets predict the expansion of current collaborations. These results provide direct evidence consistent with the social signaling role of peer tweets.

We also examine the capital market consequences of peer tweets. We find that peer tweets generate favorable market reactions not only for tweeted firms but also for tweeting firms. The latter is particularly interesting because any new developments primarily pertain to the tweeted firms. We interpret the evidence as suggesting that 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 peer tweets provide early indications of future inter-firm collaborations. We find evidence that investors respond more positively to tweets that are followed by the subsequent materialization of inter-firm collaborations. Additionally, consistent with peer tweets serving as early signals, prior peer tweets reduce

investors' surprise when strategic alliances are announced, attenuating investor reactions to subsequent announcements of strategic alliances.

Finally, we find evidence that signaling economic ties through peer tweeting has a downside, 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 peer tweets experience more 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, LSEG Institutional 13F Holdings, 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 non-negative peer tweet during the year, and zero otherwise. A peer tweet is classified as non-negative if the tweeting firm expresses at least as many positive as negative words about the tweeted firm in the tweet, based on the Loughran and McDonald (2011) financial dictionary.
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, and zero otherwise.
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 in a given year, measured for the prior year.

Variables in tests of future inter-firm collaborations (Table 4, Table OA1, Table OA2):

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 the next three years, and zero otherwise.
Sales Percent	The average percentage of sales from the supplier firm to the customer firm in the next three years.
Peer Tweet Num	The number of non-negative 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.
Peer Tweet Num Alt	The number of return-based non-negative peer tweets between the firm pair during the year. A peer tweet is classified as return-based non-negative if the market-adjusted abnormal return for the tweeted firm on the tweeting day is non-negative.

Variables in tests of market reactions around peer tweets (Table 5, Table 8, Table 9):

Variable	Definition
[0, 0] Ret VW tweeting	CARs to tweeting firms or PSM-matched non-tweeting peer firms on the non-negative peer tweeting day, adjusted by the value-weighted market portfolio.

[0, 0] Ret EW tweeting	CARs to tweeting firms or PSM-matched non-tweeting peer firms on the non-negative peer tweeting day, adjusted by the equal-weighted market portfolio.
Tweeting Firm	An indicator variable equal to one if the firm is the tweeting firm, and zero otherwise.

Variables in tests of anticipation effect (Table 6):

Variable	Definition
[0, 0] Ret VW tweet	The summation of CARs to tweeted and tweeting firms on the non-negative peer tweeting day, adjusted by the value-weighted market portfolio.
[0, 0] Ret EW tweet	The summation of CARs to tweeted and tweeting firms on the non-negative peer tweeting day, adjusted by the equal-weighted market portfolio.
Future Collaboration	An indicator variable equal to one if the tweeting and tweeted firms form collaborations within three years after the non-negative peer tweet, and zero otherwise.
[0, 0] Ret VW alliance	The summation of CARs to the firm pair on their strategic alliance announcement day, adjusted by the value-weighted market portfolio.
[0, 0] Ret EW alliance	The summation of CARs to the firm pair on their strategic alliance announcement day, adjusted by the equal-weighted market portfolio.
Peer Tweet Num	The number of non-negative peer tweets between the firm pair within the past three years prior to its strategic alliance announcement.

Variables in tests of market reactions around negative earnings guidance 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 non-negative peer tweets about the tweeted firm posted by the potential tweeting firm within 90 days prior to tweeted firm's management earnings guidance.

Variables in tests of stock return co-movement around peer tweets (Table 10):

Variable	Definition
Return Comovement	The Pearson correlation coefficient between daily stock returns of a firm pair over a 90-day window.
After Peer Tweet	An indicator variable equal to one for post-tweet observations, and zero otherwise.

Appendix B
Examples of Peer Tweets

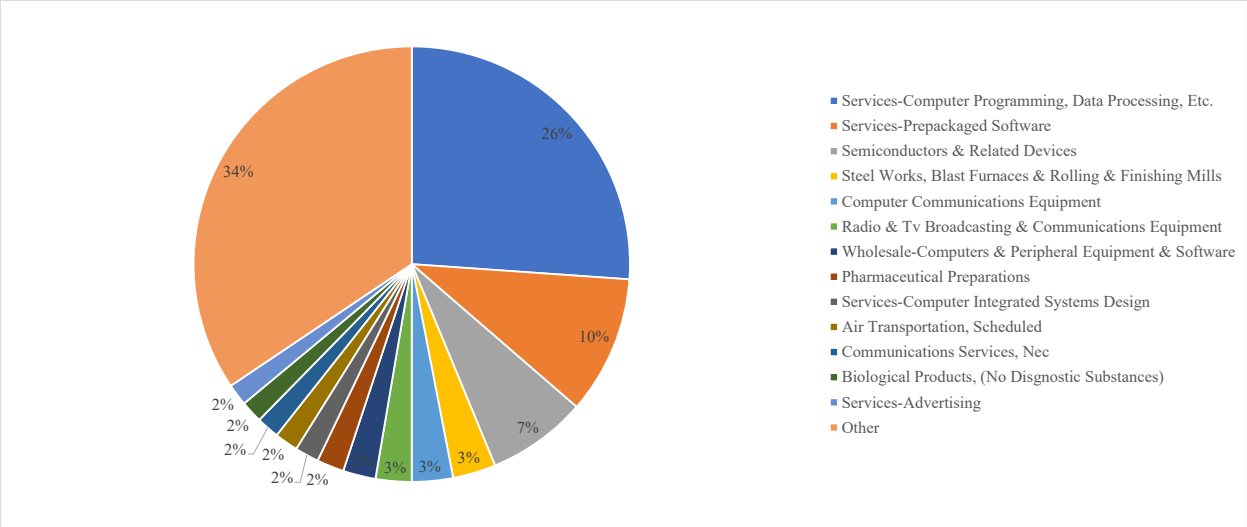
This appendix lists examples of peer tweets in our sample, in chronological order. We include the name of the tweeting firm, the name of the tweeted firm, the tweeting date of the peer tweet, and the tweet content along with the actual tweet link. We classify a peer tweet as non-negative if the tweeting firm expresses at least as many positive as negative words about the tweeted firm in the tweet, according to the financial dictionary of Loughran and McDonald (2011). All tweets were collected as of January 10, 2024.

Tweeting Firm	Tweeted Firm	Tweeting Day	Tweet Content
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)
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)
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)
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)
CA Inc	Cisco Systems Inc	November 6, 2013	@AndiMann describes @Cisco's approach 2 simplification & automation of networking infrastructure http://bit.ly/1fjwf3K #BigData (tweet link: https://x.com/CAinc/status/398198365244362752)
Lam Research Corp	Ford Motor Co	March 3, 2016	@Ford's new #wearables lab is pioneering in-car #HealthTech: http://for.tn/216QpEr #ConnectedDevices #IoT (tweet link: https://x.com/LamResearch/status/705510817316220928)
Imperial Oil Ltd	Exxon Mobil Corp	April 2, 2018	Check out @ExxonMobil's long-term view on energy supply & demand - look down the road and get an idea of what may be in store for us in terms of #energy supply, demand, emissions and how essential energy is to our everyday lives. https://exxonmobil.co/1yrlOTb #oilandgas (tweet link: https://x.com/ImperialOil/status/980886976588013568)
Boingo Wireless Inc	Tripadvisor Inc	February 4, 2014	Revamped flights search from @TripAdvisor helps find lowest fares & gives detailed 411 on in-flight amenities #PaxEx http://ow.ly/th9FX (tweet link: https://x.com/boingo/status/430799203175260160)

Figure 1
Sample Distribution of 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 SIC four-digit industry sectors of tweeted firms. The sample comprises 18,295 peer tweets from years 2008-2023.

Panel A: By Tweeting Firms' Industry Sectors



Panel B: By Tweeted Firms' Industry Sectors

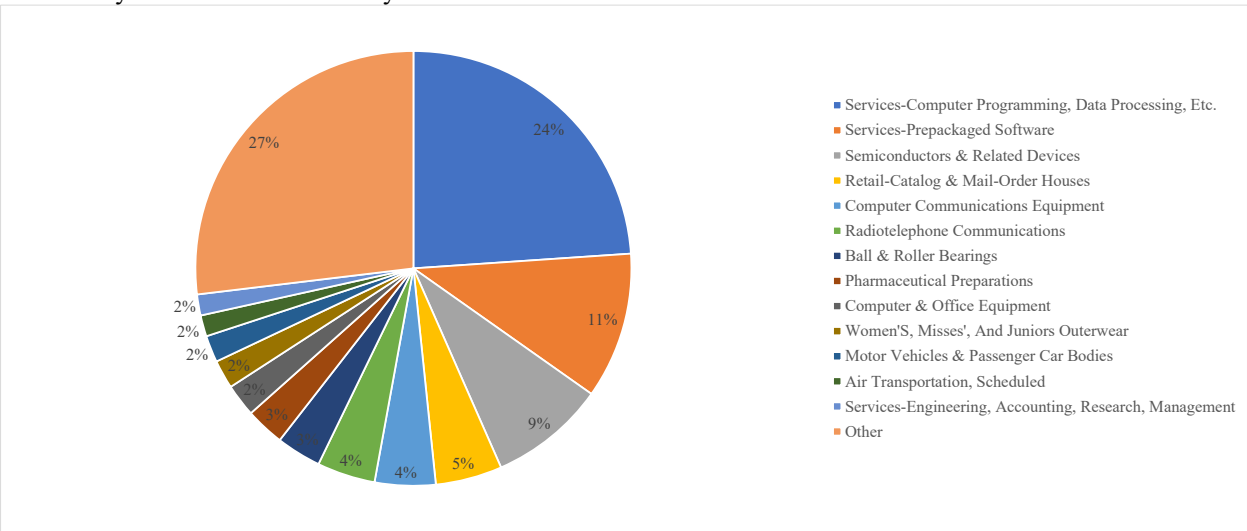


Table 1
Sample Distribution of Peer Tweets

Panel A presents the top ten tweeting industries, the number of 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 peer tweets associated with these firms. The sample comprises 18,295 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 Peer Tweets	Tweeted SIC-4 Industry Code (Top Three)		
1	7370 Services-Computer Programming, Data Processing, Etc.	4,777	7370	7372	5961
2	7372 Services-Prepackaged Software	1,877	7370	7372	3674
3	3674 Semiconductors & Related Devices	1,353	3674	7372	7370
4	3310 Steel Works, Blast Furnaces & Rolling & Finishing Mills	584	3562	3711	NA
5	3576 Computer Communications Equipment	557	7370	7372	3576
6	3663 Radio & TV Broadcasting & Communications Equipment	487	4812	3576	3674
7	5045 Wholesale-Computers & Peripheral Equipment & Software	443	3570	7372	3576
8	2834 Pharmaceutical Preparations	369	2834	2836	7370
9	7373 Services-Computer Integrated Systems Design	326	7370	7372	3576
10	4512 Air Transportation, Scheduled	319	4512	4513	4899

Panel B: Top Ten Tweeting and Tweeted Firms

Rank	Tweeting Firm	Number of Peer Tweets	Tweeted Firm	Number of Peer Tweets
1	Channeladvisor Corp	737	Microsoft Corp	1,257
2	Haynes International Inc	583	Meta Platforms Inc	1,115
3	CDW Corp	259	Cisco Systems Inc	739
4	Comscore Inc	244	Twitter Inc	691
5	Gen Digital Inc	232	Intel Corp	656
6	Aviat Networks Inc	224	Verizon Communications Inc	650
7	Virtusa Corp	213	IBM Corp	629
8	Xilinx Inc	210	Timken Co	610
9	Support.com Inc	203	Amazon.com Inc	553
10	Boingo Wireless Inc	198	HP Inc	435

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 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	18,125	13,087.799	36,749.807	316.999	1,295.301	6,770.595
Firm 1 Asset Ln	18,106	7.263	2.115	5.692	7.058	8.743
Firm 1 Sales Growth	18,056	0.109	0.264	-0.017	0.071	0.185
Firm 1 Loss	18,125	0.351	0.477	0.000	0.000	1.000
Firm 1 ROA	18,106	-0.010	0.164	-0.054	0.029	0.080
Firm 1 PPE	18,105	0.171	0.185	0.056	0.095	0.199
Firm 1 Lev	17,669	0.174	0.189	0.002	0.135	0.287
Firm 1 R&D	18,106	0.089	0.096	0.000	0.069	0.135

Panel B: Tweeted Firms

Variables	N	Mean	SD	P25	P50	P75
Firm 2 Asset	18,160	60,407.884	73,671.747	3,076.692	22,644.033	103,206.000
Firm 2 Asset Ln	18,155	9.562	2.131	7.966	9.813	11.433
Firm 2 Sales Growth	18,127	0.121	0.229	-0.009	0.063	0.198
Firm 2 Loss	18,160	0.169	0.375	0.000	0.000	0.000
Firm 2 ROA	18,155	0.049	0.131	0.016	0.065	0.109
Firm 2 PPE	18,155	0.195	0.184	0.070	0.115	0.277
Firm 2 Lev	18,070	0.209	0.153	0.103	0.199	0.293
Firm 2 R&D	18,155	0.079	0.082	0.009	0.061	0.119

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	18,125	13,087.799	18,160	60,407.884	-47,320.085***
Asset Ln	18,106	7.263	18,155	9.562	-2.299***
Sales Growth	18,056	0.109	18,127	0.121	-0.012***
Loss	18,125	0.351	18,160	0.169	0.182***
ROA	18,106	-0.010	18,155	0.049	-0.059***
PPE	18,105	0.171	18,155	0.195	-0.024***
Lev	17,669	0.174	18,070	0.209	-0.035***
R&D	18,106	0.089	18,155	0.079	0.010***

Table 3
Determinants of Peer Tweets

This table presents the results examining the determinants of peer tweets. The dependent variable, *Peer Tweet Dummy*, is an indicator variable equal to one if the firm pair has at least one 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 both firms' 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 both firms. *, **, *** 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	+	0.004***	0.003***
		(6.84)	(5.59)
Common Owner	+	0.001***	0.002***
		(4.48)	(3.92)
Firm 1 Leader	+	0.002***	0.002***
		(4.00)	(2.70)
Firm 2 Leader	+	0.010***	0.012***
		(4.14)	(3.82)
Ln (Firm 2/Firm 1 Market Cap)	+	0.000***	0.001***
		(3.63)	(3.19)
Firm 1 Lit Risk KS	+	0.000	
		(0.71)	
Firm 2 Lit Risk KS	+	0.000***	
		(3.04)	
Firm 1 Lit Risk KY	+		0.000***
			(3.53)
Firm 2 Lit Risk KY	+		0.001***
			(4.40)
Firm 2 Loss		-0.001**	-0.001**
		(-2.55)	(-2.29)
Firm 2 ROA		-0.002***	-0.003***
		(-3.36)	(-3.17)
Firm 1 MTB		0.000*	0.000
		(1.75)	(1.33)
Firm 2 MTB		0.000	0.000*
		(1.28)	(1.75)
Firm 1 Sale Growth		0.000	0.000
		(1.28)	(0.79)
Firm 2 Sale Growth		0.000	0.000
		(1.01)	(1.02)
Firm 1 Tweet Intensity		0.001***	0.001***
		(6.87)	(6.41)
Firm 2 Tweet Intensity		0.001***	0.001***
		(4.25)	(3.95)
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		0.021	0.025

Table 4

Information Content: Peer Tweets and Future Collaborations

This table presents the results examining whether peer tweets predict future inter-firm collaborations. The sample consists of firm-pair-year observations from years 2008-2023. The independent variable of interest, *Peer Tweet Num*, is the number of peer tweets between the firm pair in year *t*. Panel A presents the results examining the association between peer tweets and future inter-firm collaborations. Panel B presents the results examining the association between peer tweets and the expansion of existing inter-firm 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 the 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 the 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 peer tweet during the sample period. Columns 1 and 3 include year and both firm fixed effects, 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: Peer Tweets and Future Collaborations

Dependent variable:		*Form Relation*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	+	0.006***	0.002**	0.005***	0.002**
		(4.28)	(2.37)	(3.73)	(2.06)
Firm 1 Asset Ln		0.001**	0.001***	0.009**	0.011***
		(2.39)	(2.85)	(2.31)	(2.84)
Firm 2 Asset Ln		0.001**	0.001***	0.009**	0.011***
		(2.39)	(2.85)	(2.31)	(2.84)
Firm 1 Sale Growth		-0.000	-0.000	0.013**	0.010*
		(-0.18)	(-0.39)	(2.36)	(1.84)
Firm 2 Sale Growth		-0.000	-0.000	0.013**	0.010*
		(-0.18)	(-0.39)	(2.36)	(1.84)
Firm 1 Loss		-0.001**	-0.001*	-0.012**	-0.010*
		(-2.53)	(-1.74)	(-2.00)	(-1.84)
Firm 2 Loss		-0.001**	-0.001*	-0.012**	-0.010*
		(-2.53)	(-1.74)	(-2.00)	(-1.84)
Firm 1 ROA		-0.001	-0.000	-0.046*	-0.033
		(-1.33)	(-0.67)	(-1.72)	(-1.34)
Firm 2 ROA		-0.001	-0.000	-0.046*	-0.033
		(-1.33)	(-0.67)	(-1.72)	(-1.34)
Firm 1 Lev		0.000	0.000	0.010	0.010
		(0.40)	(0.32)	(0.48)	(0.51)
Firm 2 Lev		0.000	0.000	0.010	0.010
		(0.40)	(0.32)	(0.48)	(0.51)
Firm 1 R&D		0.000	0.005***	-0.025	-0.008
		(0.13)	(3.47)	(-0.48)	(-0.15)
Firm 2 R&D		0.000	0.005***	-0.025	-0.008
		(0.13)	(3.47)	(-0.48)	(-0.15)
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	57,486	57,414
Adj. R-Squared		0.048	0.359	0.156	0.337

Table 4 (continued)

Panel B: Peer Tweets and the Expansion of Existing Collaborations

Dependent variable:		*Sales Percent*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num	+	0.317***	0.197***	0.246***	0.215***
		(2.99)	(3.27)	(4.08)	(3.67)
Firm 1 Asset Ln		-0.548	-0.448	-0.145	-0.257
		(-0.76)	(-0.58)	(-0.11)	(-0.20)
Firm 2 Asset Ln		-0.544	-0.443	-0.145	-0.257
		(-0.75)	(-0.57)	(-0.11)	(-0.20)
Firm 1 Sale Growth		-0.662	-0.238	0.107	0.172
		(-1.21)	(-0.62)	(0.13)	(0.21)
Firm 2 Sale Growth		-0.670	-0.249	0.107	0.172
		(-1.22)	(-0.65)	(0.13)	(0.21)
Firm 1 Loss		-0.258	-0.330	-0.238	-0.386
		(-0.66)	(-1.17)	(-0.42)	(-0.70)
Firm 2 Loss		-0.258	-0.331	-0.238	-0.385
		(-0.66)	(-1.17)	(-0.42)	(-0.70)
Firm 1 ROA		0.343	-0.646	4.037	3.847
		(0.17)	(-0.45)	(1.57)	(1.48)
Firm 2 ROA		0.353	-0.633	4.038	3.847
		(0.17)	(-0.44)	(1.57)	(1.48)
Firm 1 Lev		-1.846	-2.139	-4.609	-5.042*
		(-0.89)	(-1.18)	(-1.48)	(-1.75)
Firm 2 Lev		-1.851	-2.132	-4.609	-5.042*
		(-0.90)	(-1.18)	(-1.48)	(-1.75)
Firm 1 R&D		4.315	2.037	2.667	2.833
		(0.91)	(0.46)	(0.23)	(0.26)
Firm 2 R&D		4.331	2.058	2.668	2.833
		(0.92)	(0.46)	(0.23)	(0.26)
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		10,770	10,522	2,676	2,662
Adj. R-Squared		0.712	0.885	0.843	0.872

Table 5
Market Reactions to Peer Tweets: Tweeted and Tweeting Firms

This table presents the results examining market reactions to tweeted and tweeting firms around peer tweets. The sample comprises 18,295 peer tweets from years 2008-2023. Panel A presents the mean market-adjusted CARs to tweeted firms around peer tweets. Panel B presents mean market-adjusted CARs to tweeting firms around peer tweets. Panel C presents mean market-adjusted CARs to non-tweeting peer firms around peer tweets, using a PSM-matched sample (i.e., one matched non-tweeting peer firm for each peer tweet). Panel D presents the regression results examining market-adjusted CARs to tweeting firms around peer tweets, using PSM-matched non-tweeting peer firms as the benchmark. In Panels A-C, column 1 (2) reports CARs adjusted by CRSP equal-weighted (value-weighted) portfolio. In Panel D, columns 1-2 use CARs adjusted by CRSP value-weighted portfolio (*[0, 0] Ret VW tweeting)* as the dependent variable, and columns 3-4 use CARs adjusted by CRSP equal-weighted portfolio (*[0, 0] Ret EW tweeting*) as the dependent variable. In Panel D, columns 2 and 4 include year and tweet fixed effects. In each panel, 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 based on standard errors clustered by tweeting date.

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

	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	0.0872***	0.0832**
[0, 1]	0.1349***	0.1247***
[0, 2]	0.1670***	0.1539***
Pre-tweeting day [-1, -1]	0.0377	0.0305
No. of observations	18,295	18,295

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

	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	0.0816***	0.0775***
[0, 1]	0.1009**	0.0907**
[0, 2]	0.1042**	0.0911*
Pre-tweeting day [-1, -1]	0.0174	0.0103
No. of observations	18,295	18,295

Panel C: Falsification: Market-Adjusted CARs to PSM-Matched *Non-Tweeting* Peer Firms Around Peer Tweets

	CARs over the market portfolio	
	Equal-weighted	Value-weighted
Event window	(1)	(2)
[0, 0]	0.0038	-0.0002
[0, 1]	0.0255	0.0164
[0, 2]	0.0490	0.0355
Pre-tweeting day [-1, -1]	-0.0003	-0.0109
No. of observations	17,632	17,632

Table 5 (continued)

Panel D: Market-Adjusted CARs to *Tweeting* Firms Around Peer Tweets (Using PSM-Matched Non-Tweeting Peer Firms as Benchmark)

Dependent variable:		*[0, 0] Ret VW tweeting*		*[0, 0] Ret EW tweeting*	
	Pr. Sign	(1)	(2)	(3)	(4)
Tweeting Firm	+	0.076**	0.076**	0.076**	0.076**
		(2.21)	(2.21)	(2.23)	(2.23)
Constant		-0.000	-0.000	0.004	0.004
		(-0.01)	(-0.01)	(0.18)	(0.22)
Year FE		No	Yes	No	Yes
Tweet FE		No	Yes	No	Yes
S.E. clustered by date		Yes	Yes	Yes	Yes
No. of observations		35,264	35,264	35,264	35,264
Adj. R-Squared		0.000	0.055	0.000	0.050

Table 6
Further Test of Signaling: Peer Tweets and Anticipation Effect

This table presents the results examining the market anticipation of potential inter-firm collaborations implied by peer tweets. Panel A shows the results examining the future inter-firm collaborations and total market reactions to tweeted and tweeting firms around peer tweets. Panel B shows the results examining peer tweets and future strategic alliance announcement returns. In Panel A, the sample is at the peer tweet level (~18,295 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 collaborations within three years after this peer tweet, and zero otherwise. Dependent variables are the summation of market-adjusted CARs to tweeted and tweeting firms around 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 peer tweets for the firm pair during the past year 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 2 and 4 include year and both firms' SIC two-digit industry fixed effects. All variables are defined in Appendix A. In Panel A (B), the *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by tweeting date (strategic alliance announcement date). *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Collaboration Outcomes and Market Reactions to Tweeted and Tweeting Firms Around Peer Tweets

Dependent variable:		*[0, 0] Ret VW tweet*		*[0, 0] Ret EW tweet*	
	Pr. Sign	(1)	(2)	(3)	(4)
Future Collaboration	+	0.190***	0.179**	0.205***	0.185**
		(2.60)	(2.18)	(2.81)	(2.24)
Constant		0.068*	0.071*	0.071*	0.076*
		(1.65)	(1.73)	(1.78)	(1.90)
Year FE		No	Yes	No	Yes
Firm 1 Ind and Firm 2 Ind FE		No	Yes	No	Yes
S.E. clustered by date		Yes	Yes	Yes	Yes
No. of observations		18,295	18,291	18,295	18,291
Adj. R-Squared		0.001	0.007	0.001	0.007

Panel B: 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	-	-0.133**	-0.089*	-0.126**	-0.085*
		(-2.12)	(-1.70)	(-2.15)	(-1.69)
Constant		1.513***	1.510***	1.547***	1.545***
		(6.10)	(6.17)	(6.21)	(6.28)
Year FE		No	Yes	No	Yes
Firm 1 Ind and Firm 2 Ind FE		No	Yes	No	Yes
S.E. clustered by date		Yes	Yes	Yes	Yes
No. of observations		9,450	9,448	9,450	9,448
Adj. R-Squared		0.000	0.011	0.000	0.010

Table 7

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

This table presents the results examining the market reactions to tweeting firms around negative earnings guidance 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 peer tweets posted by the tweeting firm during the 90 days before its tweeted firm's negative management earnings guidance. Columns 2 and 4 include year and tweeting firm's 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 management earnings guidance date. *, **, *** 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	-	-0.038**	-0.040**	-0.027**	-0.032**
		(-2.28)	(-2.38)	(-1.98)	(-2.21)
Constant		-0.097***	-0.097***	-0.076***	-0.076***
		(-3.01)	(-3.11)	(-2.86)	(-2.95)
Year FE		No	Yes	No	Yes
Ind FE		No	Yes	No	Yes
S.E. clustered by date		Yes	Yes	Yes	Yes
No. of observations		442,757	442,757	442,757	442,757
Adj. R-Squared		0.000	0.002	0.000	0.002

Table 8
Additional Analysis: Positive versus Neutral Peer Tweets

This table presents the results comparing positive and neutral peer tweets. Panels A-B present mean market-adjusted CARs to tweeted and tweeting firms around positive versus neutral peer tweets. The sample comprises 5,478 positive peer tweets and 12,817 neutral peer tweets from years 2008-2023. Columns 1, 3, and 5 (Columns 2, 4, and 6) report CARs adjusted by CRSP equal-weighted (value-weighted) portfolio. CARs are multiplied by 100 for ease of interpretation. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test based on standard errors clustered by tweeting date.

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

Tweet sample:	CARs over the market portfolio					
	Positive		Neutral		Positive - Neutral	
	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
Event window	(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
[0, 0]	0.1424***	0.1383***	0.0637	0.0596	0.0787	0.0787
[0, 1]	0.1623***	0.1604***	0.1232***	0.1094**	0.0391	0.0510
[0, 2]	0.1755**	0.1775***	0.1634***	0.1439***	0.0121	0.0336
Pre-tweeting day [-1, -1]	0.0285	0.0211	0.0416	0.0345	-0.0131	-0.0134
No. of observations	5,478	5,478	12,817	12,817		

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

Tweet sample:	CARs over the market portfolio					
	Positive		Neutral		Positive - Neutral	
	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
Event window	(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
[0, 0]	0.0819*	0.0779*	0.0814**	0.0773**	0.0005	0.0005
[0, 1]	0.0945*	0.0927	0.1036**	0.0898*	-0.0091	0.0028
[0, 2]	0.1796***	0.1816***	0.0719	0.0524	0.1077	0.1292
Pre-tweeting day [-1, -1]	0.0362	0.0288	0.0094	0.0023	0.0268	0.0264
No. of observations	5,478	5,478	12,817	12,817		

Table 9

Additional Analysis: Signaling Value of Peer Tweets: Socially Active versus Inactive Firms

This table presents the results comparing peer tweets issued by socially inactive versus socially active firms. Panels A-B present mean market-adjusted CARs to tweeted firms and tweeting firms around peer tweets issued by socially inactive versus socially active firms. Socially active and socially inactive firms are classified based on whether the tweeting firm's tweeting intensity in the prior year is above or below the sample median. The sample consists of 9,353 peer tweets issued by socially inactive firms and 8,942 peer tweets issued by socially active firms from years 2008-2023. Columns 1, 3, and 5 (Columns 2, 4, and 6) report CARs adjusted by CRSP equal-weighted (value-weighted) portfolios. 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 based on standard errors clustered by tweeting date.

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

Tweet sample:	CARs over the market portfolio					
	Inactive		Active		Inactive - Active	
	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
Event window	(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
[0, 0]	0.1494***	0.1485***	0.0222	0.0148	0.1272*	0.1337**
[0, 1]	0.1940***	0.1912***	0.0731	0.0551	0.1209	0.1361*
[0, 2]	0.2183***	0.2192***	0.1134*	0.0857	0.1049	0.1335
Pre-tweeting day [-1, -1]	0.0546	0.0510	0.0200	0.0091	0.0346	0.0419
No. of observations	9,353	9,353	8,942	8,942		

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

Tweet sample:	CARs over the market portfolio					
	Inactive		Active		Inactive - Active	
	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted	Equal-weighted	Value-weighted
Event window	(3)	(4)	(1)	(2)	(1) - (3)	(2) - (4)
[0, 0]	0.1371***	0.1362***	0.0235	0.0161	0.1136**	0.1202**
[0, 1]	0.1892***	0.1864***	0.0085	-0.0095	0.1807**	0.1959**
[0, 2]	0.2099***	0.2108***	-0.0064	-0.0341	0.2163**	0.2449***
Pre-tweeting day [-1, -1]	-0.0080	-0.0116	0.0440	0.0331	-0.0520	-0.0447
No. of observations	9,353	9,353	8,942	8,942		

Table 10

Additional Analysis: Alternative Measure of Economic Connections: Stock Return Co-Movement

This table presents the results examining the association between pairwise stock return co-movement and peer tweets. The sample consists of firm-pair observations from 2008 to 2023. For each tweet, the sample includes two firm-pair observations: one measuring stock return co-movement over days [-90, -1] (pre-tweet observation) and the other over days [1, 90] (post-tweet observation). The independent variable of interest, *After Peer Tweet*, is an indicator variable equal to one for post-tweet observations. The dependent variable, *Return Co-movement*, is measured as the Pearson correlation coefficient between daily stock returns of a firm pair over a 90-day window. To ensure clean pre- and post-tweet windows, the first sample (Columns 1-2) excludes peer tweets preceded by another peer tweet involving the same firm pair within the prior 90 days. The second sample (Columns 3 and 4) imposes a stricter restriction by retaining only the first peer tweet for each firm pair during the sample period. Columns 1 and 3 include year fixed effects, 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.

Dependent variable:		*Return Comovement*			
	Pr. Sign	(1)	(2)	(3)	(4)
After Peer Tweet	+	0.004*	0.004*	0.008**	0.008**
		(1.93)	(1.93)	(2.18)	(2.18)
Sample		I	I	II	II
Year FE		Yes	Yes	Yes	Yes
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		15,560	15,560	6,944	6,944
Adj. R-Squared		0.028	0.566	0.039	0.628

Online Appendix for
"Beyond Disclosure: Signaling Corporate Ties on Social Media"

Table OA1
Alternative Measure of Peer Tweets: Indicator Variable of Tone-Based Non-Negative Peer Tweets

This table presents main results using an indicator variable of tone-based non-negative peer tweets as a measure of peer tweets. 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 peer tweet during the year, and zero otherwise. Panel A presents the results examining peer tweets and future inter-firm collaborations. Panel B presents the results examining peer tweets and the expansion of existing inter-firm 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 the 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 the 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 peer tweet during the sample period. Columns 1 and 3 include year and both firm fixed effects, 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: Peer Tweets and Future Collaborations

Dependent variable:		*Form Relation*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Dummy	+	0.063***	0.017***	0.030***	0.010***
		(10.78)	(5.01)	(6.15)	(2.88)
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	57,486	57,414
Adj. R-Squared		0.049	0.359	0.155	0.337

Panel B: Peer Tweets and the Expansion of Existing Collaborations

Dependent variable:		*Sales Percent*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Dummy	+	1.722***	0.416	0.887***	0.504*
		(2.66)	(1.06)	(2.90)	(1.73)
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		10,770	10,522	2,676	2,662
Adj. R-Squared		0.712	0.885	0.843	0.871

Table OA2

Alternative Measure of Peer Tweets: The Number of Return-Based Non-Negative Peer Tweets

This table presents main results using the number of return-based non-negative peer tweets as a measure of peer tweets. The sample consists of firm-pair-year observations from years 2008-2023. The independent variable of interest, *Peer Tweet Num*, is the number of peer tweets for the firm pair during the year. Panel A presents the results examining peer tweets and future inter-firm collaborations. Panel B presents the results examining peer tweets and the expansion of existing inter-firm 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 the 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 the 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 peer tweet during the sample period. Columns 1 and 3 include year and both firm fixed effects, 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: Peer Tweets and Future Collaborations

Dependent variable:		*Form Relation*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num Alt	+	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: Peer Tweets and Expansion of Existing Collaborations

Dependent variable:		*Sales Percent*			
	Pr. Sign	(1)	(2)	(3)	(4)
Peer Tweet Num Alt	+	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