RIETI Discussion Paper Series 24-E-077

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RIETI Discussion Paper Series 24-E-077
November 2024

Market Reaction to News Flows in Supply Chain Networks[1]

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Abstract

This study examines how positive and negative news about firms affects their stock prices and, moreover, how it affects stock prices of the firms' suppliers and clients, using a large sample of publicly listed firms around the world and another of Japanese listed firms. The level of positiveness and negativeness of each news article is determined by FinBERT, a natural language processing model fine-tuned specifically for financial information. Supply chains of firms across the world are identified mostly by financial statements, while those of Japanese firms are taken from large-scale firm-level surveys. We find that positive news increases the change rate of stock prices of firms mentioned in the news before its disclosure, most likely because of diffusion of information through private channels. Positive news also raises stock prices of the firms' suppliers and clients before its disclosure, confirming propagation of market values through supply chains. In addition, we generally find a larger post-news effect on stock prices of the mentioned firms and their suppliers and clients than the pre-news effect. The positive difference between the post- and pre-news effects can be considered as the net effect of the disclosure of positive news, controlling for information diffusion through private channels. However, the post-news effect on suppliers and clients in Japan is smaller than the pre-news effect, which is the opposite result to non-domestic firms from around the world.

Keywords: Production Network; Stock Price; News; Propagation; Large Language Model; Sentiment
JEL classification:L14

[1]This study is conducted as a part of the Project "Research on Relationships between Economic Networks and National Security" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). The draft of this paper was presented at the DP seminar of RIETI. This study utilizes Trade and Industry and the Company Information Database and Company Linkage Database collected by Tokyo Shoko Research. The authors are grateful for the financial support of JSPS KAKENHI Grant Numbers JP24K00247, JP24K01108, JP23K25520, JP22K18533, JP23K23020, JP23K20626, JST PRESTO Grant Number JPMJPR21R2, and the Asahi Glass Foundation. This research used the computational resources of the supercomputer Fugaku (the evaluation environment in the trial phase) provided by the RIKEN Center for Computational Science.

1 Introduction

Firms interact with and influence each other through various types of networks. Major firm networks that are found to play a significant role in firms' behaviors and performance in the literature include financial networks through ownership[1–3] and knowledge networks through research collaboration.[4–8] Another type of network recently paid attention in the academic literature and business and policy fields is supply chains formed through transactions of materials, parts, and components.[9,10] One reason for the growing attention is that supply chains have expanded globally, linking firms in the world within a small number of steps with each other.[11]

Global supply chains have rapidly expanded because interconnected firms through supply chains can greatly benefit from the network. Most notably, supply chains can empower firms by enhancing efficiency of production processes and thus optimizing firms' economic performance.[12,13] For instance, by procuring and manufacturing different goods in various locations based on each location's comparative advantages and cost effectiveness, firms can streamline their operations as a network, ultimately leading to reductions in production costs and improvements in productivity.[14] Moreover, it is often evidenced that productivity spills over through supply chains from upstream suppliers to downstream client firms because of high-quality materials, parts, components, and services and from downstream to upstream firms because of learning of knowledge and technology.[7,15,16]

Conversely, supply chains can be a channel of negative shocks that aggravate firm performance, particularly once supply chains are disrupted due to unexpected events, such as natural disasters and geopolitical instability.[17–19] Such negative shocks examined in the literature include the Great East Japan Earthquake in 2011,[20] the massive flood in Thailand in 2011,[21] the COVID-19 pandemic from 2020 to 2022,[22], and the Russia-Ukraine war that started in 2022.[23]

Therefore, positive or negative shocks propagate through supply chains, affecting performance of firms linked through supply chains. Because the corporate value of publicly listed firms is evaluated in the stock market,[24–26] a shock to a firm is expected to affect not only its own stock price but also the stock prices of its suppliers and client firms. For example, when Boeing 737 MAX crashed in 2019 and 2020, the stock price of Boeing, its supplier, such as GE and Allegheny Technologies, and its clients, such as American Airlines and Southwest Airlines, dropped sharply.[27–31]. Also, a misconduct by Daihatsu Motor Co., a Japanese automobile manufacturer affiliated with Toyota, in 2023 negatively affected the stock price of Daihatsu, Toyota, and their suppliers and clients, such as Aisin.[32,33]

These examples show that the shock can propagate through supply chains and affect stock prices of firms linked through supply chains. Although previous studies have examined the direct impact of shocks to firms on their own stock prices[34–36], to the best of our knowledge, no study has investigated the diffusion of shocks to other firms' stock prices through supply chains. To fill the gap, this study examines this possible diffusion, using two large firm-level samples, one for firms across the world and the other for Japanese firms. Specifically, we test whether the level of positive and negative sentiment about a firm in a news article affects the change rate of the stock price of the firm and its suppliers and clients before and after the disclosure of the news.

We contribute to the literature by utilizing large-scale data in many respects. First, our firm-level data covers most publicly listed firms in the world and in Japan and identify detailed supply chains among them using financial statements, news articles, websites, and firm-level surveys. Second, our data on news articles are taken from the NewsArchive of Thomson Reuters and cover more than 20 million articles. Third, we employ daily stock prices of all listed firms to examine both short- and long-run effects of positive news.

Another notable contribution of this study is that we utilize sentiment analysis to determine the positiveness

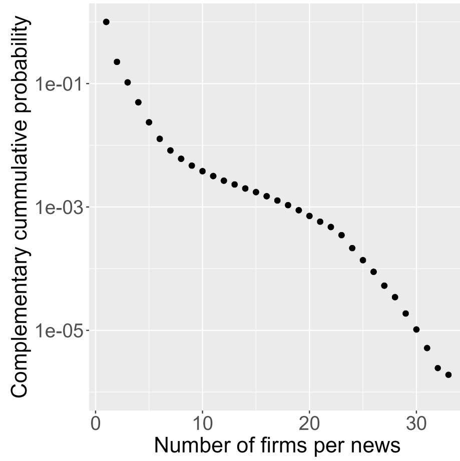


Figure 1. Distribution of the number of firms mentioned in each news article.

and negativeness of each news article. Prior research on sentiment analysis has predominantly focused on neural networks[37,38], and recently, Bidirectional Encoder Representations from Transformers (BERT)[39] has garnered the most acclaim as the state-of-the-art approach[35]. We take advantage of FinBERT,[40] a fine-tuned model of BERT particularly for financial information.

2 Data

This study utilizes four major data sources. First, our information on news relies on news articles written in English included in the NewsArchive provided by Thomson Reuters for the period 2003-2016. The information in each news article includes the date, headline, main text, International Securities Identification Numbers (ISIN) of firms mentioned in the article, and language. As we will explain later in detail, our sentiment analysis to determine how much each news article is positive or negative about firms mentioned there utilizes the main text. The average number of words in an article is 243, whereas its median is 136 and maximum is 3911. Although the total number of news articles in the NewsArchive for the period examined is 20,803,561, we focus on 3,447,425 that mention any firm publicly listed in 105 stock markets in the world. 90% of these news articles mention 3 or fewer firms, whereas the maximum number of mentioned firms in an article is 33 (Figure 1). The number of news articles that mention a particular firm during the period 2003-2016 is quite skewed. 55.6% of firms were never mentioned, while 0.1% were mentioned more than 10,000 times (Figure 2).

Second, we utilize daily stock prices of currently listed firms in stock markets in the world taken from the Eikon database provided by Refinitiv, one of the largest providers of financial markets data and infrastructure, using its Application Programming Interface (API). We drop firms listed in the past but not currently from our sample, because their stock prices are not available using the API. We particularly define the daily stock price of each firm as its closing price. In addition to stock prices of each firm, we utilize the Refinitiv index for each stock market that indicates the average of stock prices in the market to control for the market-specific time trend. The Refinitiv index is available for 105 major markets that cover 92% of listed firms worldwide.

Third, to identify global supply chains among publicly listed firms in the world, we rely on data from FactSet that cover a number of firms across the world for the period 2003-2016 obtained as of January 18, 2023. The FactSet data include major clients of each firm reported in its financial statement. The US, Japanese, and many other

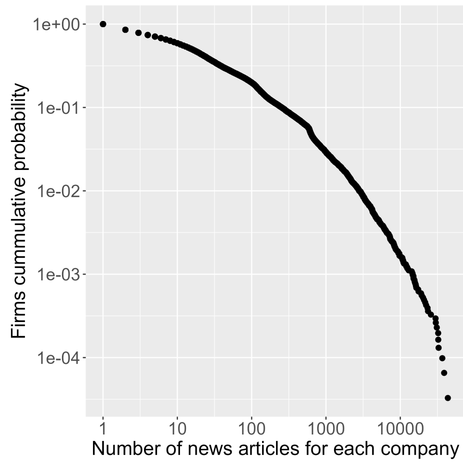


Figure 2. Distribution of the number of news articles that mentioned each firm during the period 2003-2016.

governments require every listed firm to disclose its major clients with which the sales are more than 10% of its total sales, at least in the period examined in this study[41]. Therefore, based on published financial statements and, in addition, supplemental information from news articles and web sites, FactSet identifies supply chains of listed and non-listed firms with their major partners. Table 1 shows the number of all firms (for reference) and listed firms (our sample) in the FactSet data and their supply-chain links by year. The number of firms covered in the FactSet data increased rapidly over time, because the dataset has been constructed recently and thus ignores firms in the distant past.

Finally, to identify domestic supply chains within Japan, we employ data collected by Tokyo Shoko Research (TSR) for the period 2008-2016, particularly its Company Linkage Database that covers supply chains of more than one million firms in Japan. Supply chains are captured by annual firm-level surveys by TSR that request each firm to report up to 23 suppliers and client firms of each firm. Apparently, many firms are linked with more than 23 suppliers and clients, and thus their links cannot be fully identified by their own responses. However, these links can be mostly identified by responses by their suppliers and clients. The number of firms and their supply-chain links and the corresponding number for listed firms from 2008 to 2016 are presented in Table 2.

3 Methods

Sentiment analysis using FinBERT

Our sentiment analysis to determine the degree of positiveness and negativeness of the information about the listed firms provided in each news article utilizes a natural language processing (NLP) model called FinBERT[40]. FinBERT is a variant of the Bidirectional Encoder Representations from Transformers (BERT) developed by Devlin et al. (2018)[39]. Specifically, FinBERT uses Reuters' TRC2-financial that consists of 1.8 million news articles between 2008 and 2010 and fine-tunes BERT for financial sentiment classification using Financial Phrasebank that consists of 4,845 English sentences taken from financial news in the LexisNexis database. From each news article, FinBERT generates softmax outputs for three labels, i.e., positive, neutral, and negative, which indicate the weights of the three about the firms mentioned in the article. Examples are shown in Table 3. Before conducting the sentiment analysis using FinBERT, we clean news articles by deleting URLs, line breaks, ISINs, and fixed phrases at the end. The distribution of the probabilities of positive, neutral, and negative sentiments generated by FinBERT from news

Table 1. Number of firms in the world and their supply-chain links by year

	2003	2004	2005	2006	2007	2008	2009
Firms across the world (total)							
Number of firms	9,283	9,292	9,804	10,058	10,342	10,197	10,802
Number of links	38,594	40,749	45,172	38,866	34,894	33,136	28,640
Maximum indegree	283	272	272	421	343	291	195
Maximum outdegree	255	266	249	203	159	180	156
firms across the world (listed)							
Number of firms	633	726	783	797	745	760	1,047
Number of links	1,413	1,685	1,914	1,723	1,386	1,364	1,687
Maximum indegree	31	36	30	24	22	19	17
Maximum outdegree	35	41	47	56	43	44	35

	2010	2011	2012	2013	2014	2015	2016
Firms across the world (total)							
Number of firms	17,729	24,671	28,244	31,090	40,146	53,114	64,968
Number of links	42,971	61,675	72,671	82,673	101,748	133,134	167,772
Maximum indegree	463	600	577	496	423	586	562
Maximum outdegree	162	201	206	198	256	294	378
firms across the world (listed)							
Number of firms	2,153	3,842	4,798	5,779	8,418	10,729	12,728
Number of links	4,179	8,782	12,073	15,485	22,473	31,537	42,201
Maximum indegree	27	70	115	127	161	225	277
Maximum outdegree	40	54	79	79	75	109	140

Table 2. Number of firms in Japan and their supply-chain links by year.

	2008	2009	2010	2011	2012	2013	2014	2015	2016
Japan (total)									
Number of firms	1,018,570	1,061,051	1,107,760	1,135,200	1,156,205	1,182,729	1,194,034	1,200,162	1,247,939
Number of links	4,443,677	4,644,977	4,810,967	4,925,307	4,995,612	5,090,119	5,157,181	5,209,604	5,491,417
Maximum indegree	6,751	6,976	7,069	7,332	8,398	8,787	9,520	9,948	12,016
Maximum outdegree	11,140	11,150	11,155	11,201	11,287	11,490	11,586	11,588	12,729
Japan (listed firms)									
Number of firms	3,554	3,456	3,403	3,308	3,245	3,215	3,204	3,215	3,205
Number of links	21,720	22,128	22,630	22,044	21,833	21,696	21,439	20,968	20,445
Maximum indegree	201	189	180	162	151	148	145	143	141
Maximum outdegree	305	277	259	243	225	216	201	195	190

articles about firms across the world and Japanese firms are provided in Panels (A) and (B) of Figure 3, respectively. Both panels indicate that the probability of neutral sentiment is high for many news articles followed by that of negative sentiment while news articles with a large probability of positive sentiment are fewer.

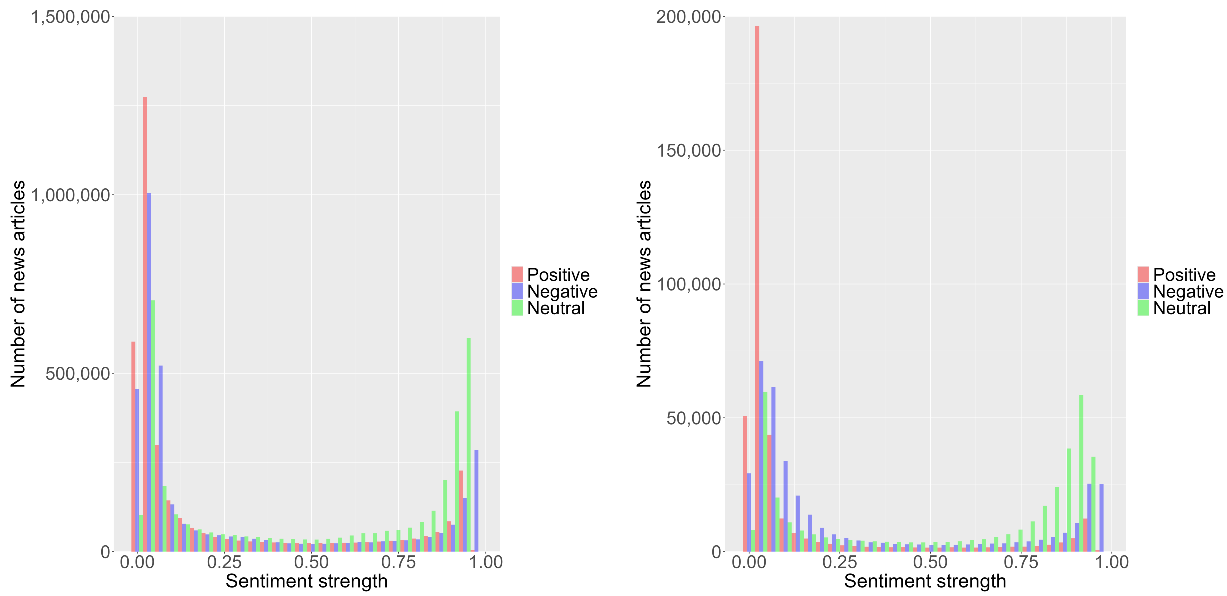
3.1 Regression analysis

Direct effect

To estimate the effect of positive and negative sentiment in news articles about particular firms on their own stock prices, we apply the probabilities of positive and negative sentiment constructed above to regression analysis. Specifically, we focus on firms mentioned by any news article and examine whether the change rate of their stock prices in a time window are affected by the level of positiveness or negativeness of the article after the article is disclosed, compared with its change rate before the disclosure. Suppose that firm i listed in stock market m is mentioned by news article n on day t. Setting the time window at w, such as 1, 5, and 30 days, we define the average daily percentage change of the stock price of firm i before and after news article n disclosed on day t in time window

Table 3. Examples of new articles and sentiments.

	Sentiment		
News article	Positive	Neutral	Negative
(Sep/11/2008) Advanced Medical Solutions Group Plc on Thursday said its silver anti-microbial wound gel had been approved by the U.S. Food & Drug Administration (FDA), sending its shares up 5 percent. ... [Source:[42]]	0.93	0.01	0.06
(Sep/11/2008) U.S. Interior Department employees who oversaw oil drilling on federal lands had sex and used illegal drugs with workers at energy companies ... [Source:[43]]	0.02	0.21	0.76
(Sep/11/2008) Amazon.com, the largest global online retailer, plans to start selling U.S.-produced wine on its website within the United States by late September or October ... [Source:[44]]	0.14	0.84	0.01



(A) Firms across the world

(B) Japanese firms

Figure 3. Distribution of the probabilities of positive, neutral, and negative sentiments in news articles generated by Fin BERT.

w, or $(\%\Delta P/P)^{pre}_{intw}$ and $(\%\Delta P/P)^{post}_{intw}$, respectively, by

$$(\%\Delta P/P)^{pre}_{intw} = (\ln \bar{P}_i[t-w, t-1] - \ln \bar{P}_i[t-2w, t-w-1])/w \times 100 \qquad \text{for the pre-news change,} \tag{1}$$

$$(\%\Delta P/P)^{post}_{intw} = (\ln \bar{P}_i[t, t+w-1] - \ln \bar{P}_i[t-w, t-1])/w \times 100 \qquad \text{for the post-news change,} \tag{2}$$

where $\bar{P}_i[s,t]$ is the average stock price of firm i between day s and t. For example, $\bar{P}_i[t-w, t-1]$ is the average stock price of firm i for w days between day $t-1$ and $t-w$. Therefore, the left-hand side of equations (1) and (2) indicates the daily percentage change of the average stock price in time window w in the pre- and post-news period, respectively. We take the average of stock prices over the time window to reduce their fluctuations. We exclude Saturdays, Sundays, and holidays from our daily observations because stock prices are not available on these days. Accordingly, for example, as shown in Figure 4, when news article n about firm i is disclosed on Friday, the 11th of June and the time window is set at 3 days, the pre-news change rate is defined as the change rate from the average

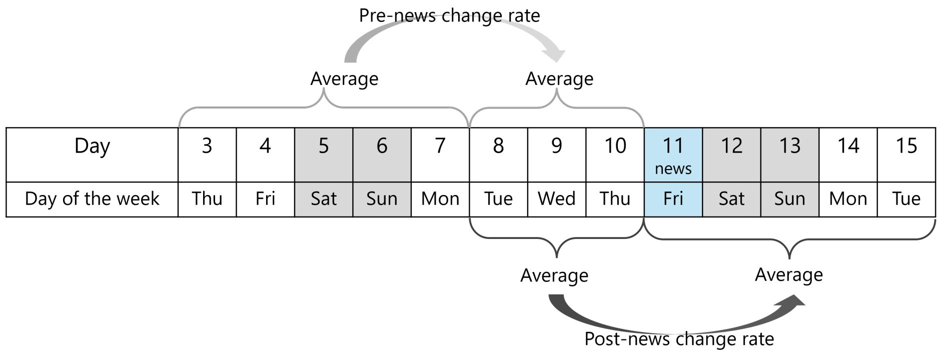


Figure 4. Definition of pre- and post-news change rate of stock prices. An example when a news article is disclosed on Friday, the 11th of June and the time window is 3 days.

stock price on June 3rd (Thursday), 4th (Friday), and 7th (Monday), skipping 5th (Saturday) and 6th (Sunday), to the average from the 8th (Tuesday) to 10th (Thursday). Similarly, the post-news change is defined as the change from the average of June 8th-10th to that of June 11th, 14th (Monday), and 15th (Tuesday).

Thus, our sample is restricted to firm-day observations before or after news articles about the firms are disclosed. In other words, the number of observations in our sample is the cumulative number of firms mentioned in news articles during the period examined multiplied by 2. Using the pre- and post-news observations, we estimate the following estimation equation:

$$(\%\Delta P/P)^{T}_{intw} = \beta^{pre}_{w}(PRE_{intw} \times NEWS_{int}) + \beta^{post}_{w}(POST_{intw} \times NEWS_{int}) + \beta_{X} X_{mntw} + \mu_{s} + \varepsilon_{intw} \text{ for } T = pre, post, \tag{3}$$

where PRE_{intw} and $POST_{intw}$ are indicator variables that take a value of one if $(\%\Delta P/P)^{T}_{intw}$ is the percentage change of the stock price of firm i before and after news article n is disclosed on day t, respectively, or $T = pre, post$. $NEWS_{int}$ represents the level of either positive or negative sentiment in news article n generated by FinBERT (Data section). X_{mntw} is the percentage change of the Refinitiv index for each stock market m that controls for the overall time trend of stock prices in the market, and μ_s is sector dummies. Sectors are defined by the North American Industry Classification System at the sub-sector level for the sample of firms across the world and by the Japan Standard Industrial Classification at the two-digit level for the sample of Japanese firms.

Accordingly, β^{post}_{w} indicates the average effect of the positiveness or negativeness of a news article on the average change rate of the stock price of the firm mentioned in the article after it is disclosed in the time window of w days, controlling for the overall trend in the market and sector-specific unobservable factors. By contrast, β^{pre}_{w} indicates any prior "effect" of the news article on the change rate of the stock price, including the possible effect of the information in the news article that diffuses in the market not through the news but through other private channels before the disclosure of the news. Such private channels include suggestions by financial companies to their clients, posts in Social Networking Services (SNS) by influencers, and word of mouth among investors. In addition, β^{pre}_{w} may include the endogeneity bias reflecting the possibility that the growth rate of the stock price of a firm that is positively mentioned by any news article is intrinsically higher than that of a firm negatively mentioned. Therefore, the net effect of the disclosure of the information by the news article on the change rate of the stock price in time window w should be given by $\beta^{post}_{w} - \beta^{pre}_{w}$[45].

We particularly estimate equation (3) for $w = 1, 2, 3, 4, 5, 30, 180, \text{and} 365$ to examine both the short- and long-run effect of positive news articles on stock prices. We hypothesize that a positive (negative) news article would accelerate (deteriorate) the change rate of the stock price of the firm mentioned in the article in the short-run, while the effect would become smaller and converge to 0 in the longer run.

It should be emphasized that this analysis is comparing firms positively mentioned in news articles with those negatively mentioned, rather than comparing firms positively mentioned and those not mentioned by news articles. We focus on the sub-sample of firms mentioned by news articles and ignore those not mentioned, because the two types of firms are most likely to be intrinsically different from each other to a great extent so that comparing the two may be associated with large endogeneity biases.

Indirect effect through supply chains

We further examine the effect of positive or negative sentiment about firms in news articles on their suppliers and clients, using similar frameworks. Specifically, when we focus on the upstream effect of news articles about firms on their suppliers, $NEWS_{int}$ in equation (3) is replaced with the probability of positive or negative sentiment in the news article that mentions not firm i but any of i's client firms. Alternatively, when we examine the downstream effect of clients' news on their clients, $NEWS_{int}$ is replace with the positive or negative index of any of suppliers of firm i. When a firm mentioned by a news article has more than one supplier or client, as shown in Tables 1 and 2, we include all the suppliers and clients in our sample. In this analysis, we compare stock prices of suppliers or clients of firms mentioned positively in news articles with those of suppliers or clients of firms mentioned negatively, as in our analysis on the direct effect on own stock prices.

We hypothesize that the effect of news articles on stock prices diffuses through supply chains. Precisely, a positive news article about a client firm would accelerate the growth in the stock price of its suppliers, in addition to its own stock price, because the market predicts an increase in demand for products of the suppliers associated with higher performance in the client firm. Also, positive news about a supplier would promote growth of its clients because of possible productivity growth of the supplier. As in the case of the direct effect, the indirect effect on suppliers and clients would be smaller in the long run than in the short run.

4 Results and Discussion

Direct effect of news articles on listed firms across the world

We start with estimating how the positiveness of news articles about firms affect percentage changes in their stock prices before and after the disclosure of news, applying equation (3) to the sample of publicly listed firms across the world mentioned by any news article. Results are presented in Table 4 and Figure 5.

In column (1) of Table 4, the estimated β_1^{pre} is 0.323 and highly significant, indicating that the probability of positive sentiment in a news article about a firm is positively correlated with the percentage change in the firm's stock price from 2 days to 1 day before the disclosure of the news. Because the positiveness measure, $NEWS$ in equation (3), ranges from 0 to 1 (Figure 3), the value of the coefficient means that the change rate of the stock price of a firm mentioned in a news article most positively ($NEWS = 1$) is 0.323% points higher than that of a firm mentioned most negatively ($NEWS = 0$) before the disclosure of the news. There are two possibilities for this positive coefficient. First, positive information included in news articles diffuses to stock markets partially through private channels before the formal disclosure of news, generating the pre-news effect. Second, stock prices of firms

Table 4. Effect of the positiveness index of news articles about firms across the world on percentage changes of their own stock prices before and after the disclosure of news for different time windows (β_w^{pre} and β_w^{post} in equation [3], respectively). Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% level, respectively. The second row from the bottom shows p values from t tests for $\beta_w^{post} - \beta_w^{pre} = 0$.

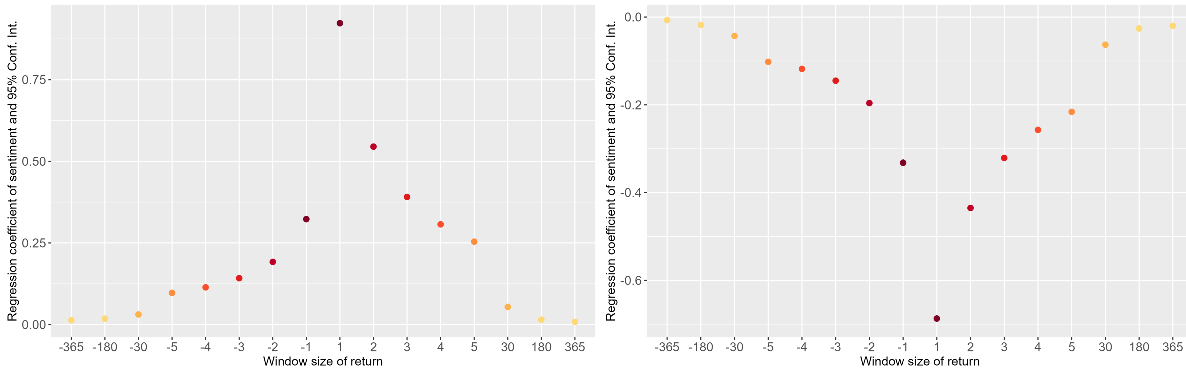
Dependent Variable:	Daily percentage change of the stock price of the firm mentioned in each news article in the pre- or post-news period							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time window (days) [w]	1	2	3	4	5	30	180	365
β_w^{pre} ($PRE_{intw} \times NEWS_{int}$)	$3.23 \times 10^{-1***}$	$1.92 \times 10^{-1***}$	$1.42 \times 10^{-1***}$	$1.14 \times 10^{-1***}$	$9.72 \times 10^{-2***}$	$3.13 \times 10^{-2***}$	$1.78 \times 10^{-2***}$	$1.33 \times 10^{-2***}$
	(4.82×10^{-3})	(2.74×10^{-3})	(2.05×10^{-3})	(1.67×10^{-3})	(1.44×10^{-3})	(4.77×10^{-4})	(1.77×10^{-4})	(1.23×10^{-4})
β_w^{post} ($POST_{intw} \times NEWS_{int}$)	$9.23 \times 10^{-1***}$	$5.45 \times 10^{-1***}$	$3.91 \times 10^{-1***}$	$3.07 \times 10^{-1***}$	$2.54 \times 10^{-1***}$	$5.41 \times 10^{-2***}$	$1.48 \times 10^{-2***}$	$7.92 \times 10^{-3***}$
	(4.89×10^{-3})	(2.75×10^{-3})	(2.05×10^{-3})	(1.68×10^{-3})	(1.44×10^{-3})	(4.77×10^{-4})	(1.76×10^{-4})	(1.21×10^{-4})
Market-specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\beta_w^{post} - \beta_w^{pre}$	0.600***	0.353***	0.249***	0.193***	0.157***	0.023***	−0.003***	−0.005
P value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of observations	9,409,978	9,543,586	9,562,439	9,565,054	9,562,897	9,460,176	8,986,209	8,546,395

positively mentioned by news articles grow faster intrinsically than those of firms negatively mentioned, leading to endogeneity biases.

Column (1) of Table 4 further finds that the estimated β_1^{post} is 0.923, indicating that the stock price of a firm mentioned in a news article most positively grows faster by 0.923% points than that of a firm mentioned most negatively after the news disclosure. The second and third rows from the bottom show $\beta_1^{post} - \beta_1^{pre}$ and the p value from a t test for the null hypothesis that the difference is 0. In column (1), the p value is close to 0, and thus we reject the null hypothesis. This result suggests that although stock prices of firms mentioned by news positively grow faster than those of firms mentioned negatively even before the disclosure of news, positive news raises stock prices of former firms more by 0.6% points after its disclosure.

These results in column (1) for the time window of 1 day generally hold in columns (2)-(5) for time windows of 2-5 and 30 days, while the post- and pre-news effects and the difference between the two decrease as the time window becomes wider. By contrast, the difference between the post- and pre-news effects is negative when the time window is 180 and 365 days, or in the long run, although the difference is quite small in size. This result implies that the intrinsic difference between firms mentioned positively and negatively by news articles is negligible. Therefore, the positive and significant difference between the post- and pre-news effects in the short run (time windows from 1 to 30 days) is mostly due to information diffusion through private channels, rather than news medias, before the disclosure of news.

Panel (A) of Figure 5 graphically demonstrates the argument above. The left half of the figure where the value on the horizontal axis is negative shows the point estimate of the pre-news effect for different time windows, whereas the right half shows the post-news effect. Although the confidence intervals are added in the figure, they are too small to be recognized. The estimated coefficients show an inverted-U shape where the coefficients are close to 0 on the left and right edges. This shape suggests the followings. The change rate of the stock price of firms positively mentioned by news articles is not intrinsically different from that of firms negatively mentioned long before the disclosure of the news. However, the change rate of the stock price of positively-mentioned firms started to increase compared with negatively-mentioned firms 30 days before the disclosure and reaches the peak 1 day after the disclosure. Then, the difference between the change rates of the stock prices of positively- and negatively-mentioned



(A) Effect of positive sentiment

(B) Effect of negative sentiment

Figure 5. Effect of the probability of positive (panel [A]) and negative (panel [B]) sentiment of news articles about firms across the world on percentage changes of their own stock prices for different time windows. Panel (A) is a graphical presentation of Table 4. When the value of the horizontal axis is negative and $-w$, the dot above the value indicates the point estimate of the pre-news effect for time window w (β_w^{pre}). When it is positive and w, the dot indicates the post-news effect for time window w (β_w^{post}). The color of the dots for time windows w and $-w$ is set to be the same so that the post- and pre-news effects can be easily compared. The confidence interval at the 5% level associated with each point estimate (dot) is shown by a vertical segment but invisible because the confidence intervals are negligible compared with the point estimate.

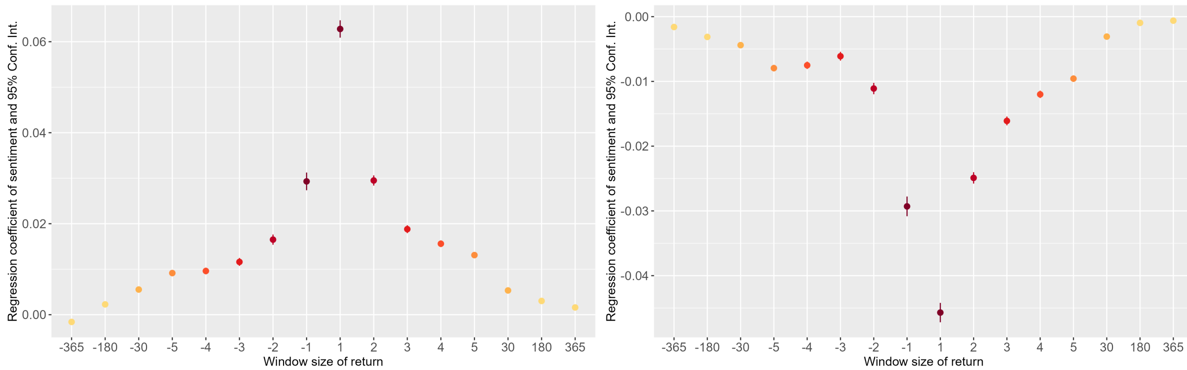
firms becomes smaller over time and converges to almost 0 180 days after the disclosure.

The effect of the probability of negative sentiment in each news article shown in Panel (B) of Figure 5 is consistent with the effect of the probability of positive sentiment in Panel (A). The effect of negative sentiment in a news article is negligible 180 days or more before its disclosure but becomes negative and significant 30 days or fewer before the disclosure, implying information diffusion through private channels. After the disclosure, the negative effect becomes larger in the absolute term, suggesting a negative net effect of the disclosure of negative news on stock prices, in addition to the negative effect through private channels.

Indirect effect on suppliers through global supply chains

Next, we examine whether positive news about a firm affects stock prices of the firm's suppliers and clients through global supply chains by estimating equation 3 where the positiveness index of news article n about firm i on day t, $NEWS_{int}$, is replaced with the index for any supplier or client of firm i.

Panels (A) and (B) of Figure 6 are the graphical presentation of the results for the effect of positive and negative news about firms, respectively, on their suppliers. Table 5 particularly shows the difference between the post- and pre-news effects of positive news and its p values, while we omit the corresponding table for the effect of negative news for brevity of presentation. The results shown in the figure and table are similar to the results for the direct effect on own firms' stock prices (Figure 5 and Table 4). The post- and pre-news effects of positive news are positive and significant, and their difference is positive and significant when the time window is narrow. These results suggest that positive news about firms raises stock prices of the firms' suppliers before the disclosure of the news due to information diffusion through private channels and raises them more after the disclosure due to the additional effect of news medias. The effect of negative news articles is opposite in the direction and similar in size to the effect of positive ones, indicating the same conclusion for negative news.



(A) Effect of positive sentiment

(B) Effect of negative sentiment

Figure 6. Effect of the probability of positive (panel [A]) and negative (panel [B]) sentiment of news articles about firms across the world on percentage changes of stock prices of their suppliers for different time windows. When the value of the horizontal axis is negative and $-w$, the dot above the value indicates the point estimate of the pre-news effect for time window w (β_w^{pre}). When it is positive and w, the dot indicates the post-news effect for time window w (β_w^{post}). The color of the dots for time windows w and $-w$ is set to be the same so that the post- and pre-news effects can be easily compared. The confidence interval at the 5% level associated with each point estimate (dot) is shown by a vertical segment.

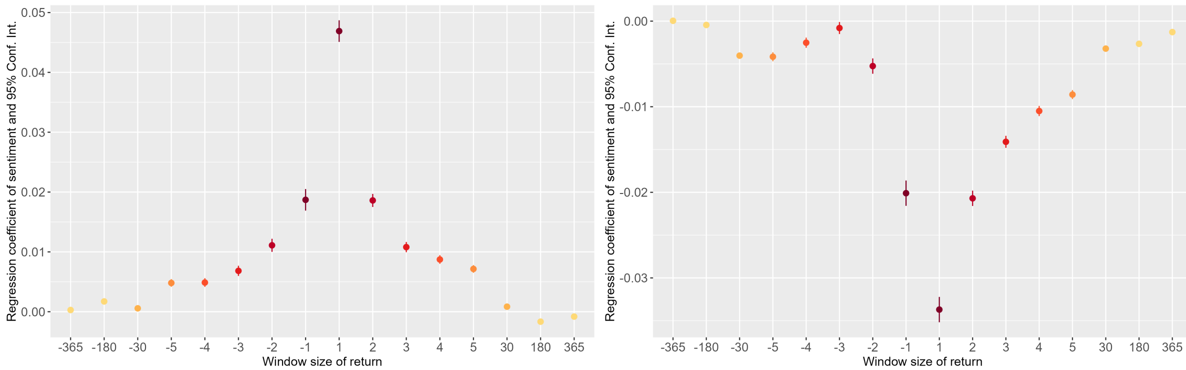
Table 5. Difference between the post- and pre-news effect of the disclosure of positive news articles about firms across the world on their suppliers' stock prices. P values are those from t tests for the null hypothesis that the difference is 0. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% level, respectively.

Time window (days)	1	2	3	4	5	30	180	365
$\beta_w^{post} - \beta_w^{pre}$	0.033***	0.013***	0.007***	0.006	0.004***	-0.00	0.001**	0.003***
P value	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00

However, there are two notable differences between the direct effect on own firms and the indirect effect on suppliers. First, the post- and pre-news effect on suppliers and their difference is substantially smaller than the direct effects and their difference. For example, the pre-news effect on suppliers for the time window of 1 days is 0.0293 (Figure 6), while the corresponding direct effect is 0.323 (Figure 5), more than 10 times larger. Similarly, the net effect of the disclosure of news, represented by $\beta_w^{post} - \beta_w^{pre}$ and shown in Table 5, is 0.033 when the time window is 1 days, while the corresponding value for the direct effect is 0.600 (Table 4). Therefore, we conclude that although positive news articles about firms affect stock prices of their suppliers, the effect on suppliers is less than 10% of the direct effect on own firms. Second, the difference between the post- and pre-news effects on suppliers is 0.033 when the time window is 1 day but becomes 0.004 when it is 5 days, meaning that the effect of the disclosure of positive news about a firm on its suppliers shrinks by 88% in 5 days. By contrast, its effect on the firm's own stock price shrinks from 0.600 to 0.157 by 74%. This comparison implies that the net effect of the disclosure of news on suppliers lasts shorter after the disclosure than the effect on own stock prices.

Indirect effect on clients through global supply chains

Similarly, we examine the effect of positive and negative news articles on stock prices of client firms and illustrate the results in Panels (A) and (B) of Figure 7, respectively. Table 6 additionally show the net effect of positive news



(A) Effect of positive sentiment

(B) Effect of negative sentiment

Figure 7. Effect of the probability of positive (panel [A]) and negative (panel [B]) sentiment of news articles about <u>firms across the world</u> on percentage changes of stock prices of their <u>clients</u> for different time windows. When the value of the horizontal axis is negative and $-w$, the dot above the value indicates the point estimate of the pre-news effect for time window w (β_w^{pre}). When it is positive and w, the dot indicates the post-news effect for time window w (β_w^{post}). The color of the dots for time windows w and $-w$ is set to be the same so that the post- and pre-news effects can be easily compared. The confidence interval at the 5% level associated with each point estimate (dot) is shown by a vertical segment.

Table 6. Difference between the post- and pre-news effect of the disclosure of positive news articles about <u>firms across the world</u> on their <u>clients</u>' stock prices. P values are those from t tests for the null hypothesis that the difference is 0. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10% level, respectively.

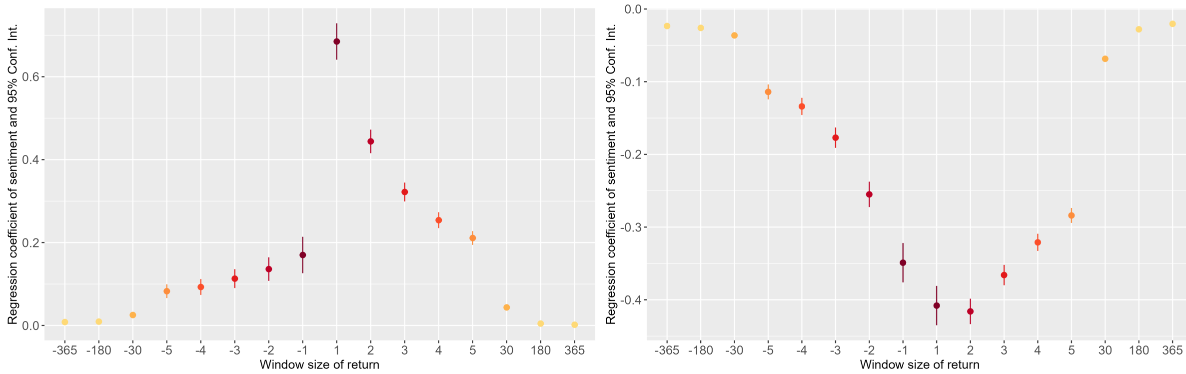
Time window (days)	1	2	3	4	5	30	180	365
$\beta_w^{post} - \beta_w^{pre}$	0.028***	0.007***	0.004***	0.004***	0.002***	0.000	−0.003**	−0.001***
P value	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00

in particular. These results are quite similar to those of the effect on suppliers shown in Figure 6 and Table 5. In summary, we find a positive (negative) and significant pre- and post-news effect of positive (negative) news and a positive (negative) and significant net effect of the disclosure of news. However, the effect of news about a firm on its clients is substantially smaller and lasts shorter than the effect on its own.

Effect on Japanese firms

We further use another sample that focuses on Japanese listed firms. The results for the direct effect of positive and negative news articles on Japanese firms' own stock prices shown in Figure 8 are qualitatively and quantitatively similar to those using the sample of firms across the world shown in Figure 5. One subtle difference is that in Figure 8 for Japan, the post-news effect of negative news using the time window of 2 days is larger in the absolute term than that using the time window of 1 day, while Figure 5 for firms in the world shows the opposite. This finding suggests that the market reaction to negative news in Japan is slower than that to positive news in Japan and to positive and negative news in the world.

In addition, we examine the indirect effect of news articles about Japanese firms on stock prices of their suppliers and clients. A notable difference between this analysis on Japanese firms and the previous one on firms across the world is that more detailed domestic supply chains are identified based on firm-level surveys in the former than in



(A) Effect of positive sentiment (B) Effect of negative sentiment

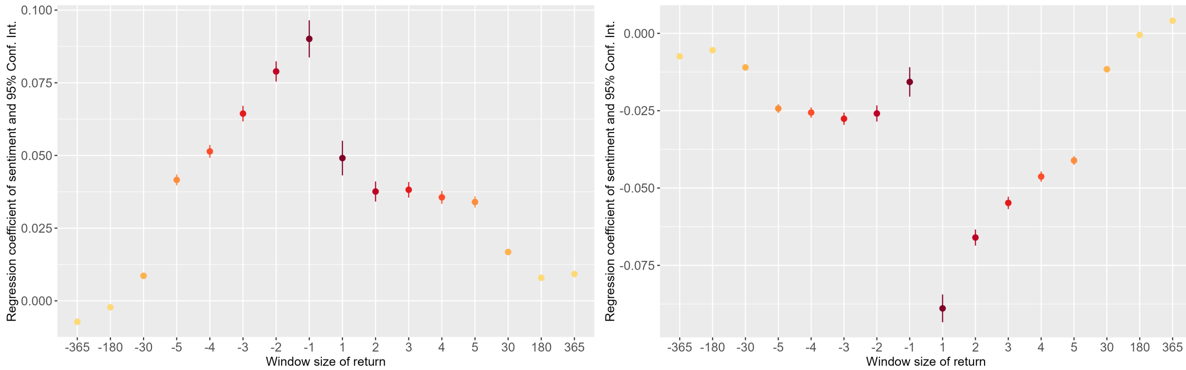
Figure 8. Effect of the probability of positive (panel [A]) and negative (panel [B]) sentiment of news articles about Japanese firms on percentage changes of their own stock prices for different time windows. When the value of the horizontal axis is negative and $-w$, the dot above the value indicates the point estimate of the pre-news effect for time window w (β_w^{pre}). When it is positive and w, the dot indicates the post-news effect for time window w (β_w^{post}). The color of the dots for time windows w and $-w$ is set to be the same so that the post- and pre-news effects can be easily compared. The confidence interval at the 5% level associated with each point estimate (dot) is shown by a vertical segment.

the latter that mostly relies on financial statements (Data Section). Therefore, the average number of supply chain links for each Japanese firm in 2016 is 6.4, while that for each firm in the world is 3.3 (Tables 1 and 2).

The results for the effect of positive and negative news on suppliers are demonstrated in Panels (A) and (B) of Figure 9, respectively, showing three notable differences from the previous results in Figure 6. First, the pre-news effect due to information diffusion through private channels is generally larger for Japanese firms than for others. For example, using the time window of 1 and 2 days, the pre-news effect of positive news on suppliers is 0.0090 and 0.0079 for Japan but 0.0029 and 0.0017 for others, respectively. Similarly, the post-news effect of negative news using the same windows is -0.0089 and -0.0066 for Japan and -0.0046 and -0.0025 for others, respectively.

Second, the post-news effect of positive news is smaller than its pre-news effect (Panel [A] of Figure 9), although the post-news effect is always larger in size than the pre-news effect in the previous results. This finding implies that although positive information about a firm tends to diffuse actively through private channels, such as suggestions of financial companies, SNS, and word of mouth, before its disclosure by a news article and increase stock prices of suppliers of the firm. However, once the positive information is disclosed in a news article, the growth rate of the suppliers' stock prices declines compared with that in the pre-news period. In other words, the net effect of the disclosure of positive news about a Japanese on stock prices of its suppliers is negative, although the previous results found the opposite.

Finally, we do observe that the post-news effect is larger than the pre-news effect in the case of negative news, as in the previous results (Panel [B] of Figure 9). However, the pre-news effect of negative news for the time window of 1 day is smaller in the absolute term than that for the longer time window of 2-5 days, although the previous result for firms across the world showed the opposite (Panel [B] of Figure 6). This, combined with the large negative post-news effect for the time window of 1 day, implies that the disclosure of negative information about a firm by a news article affects stock prices of its suppliers more substantially than diffusion of the information through private channels.



(A) Effect of positive sentiment

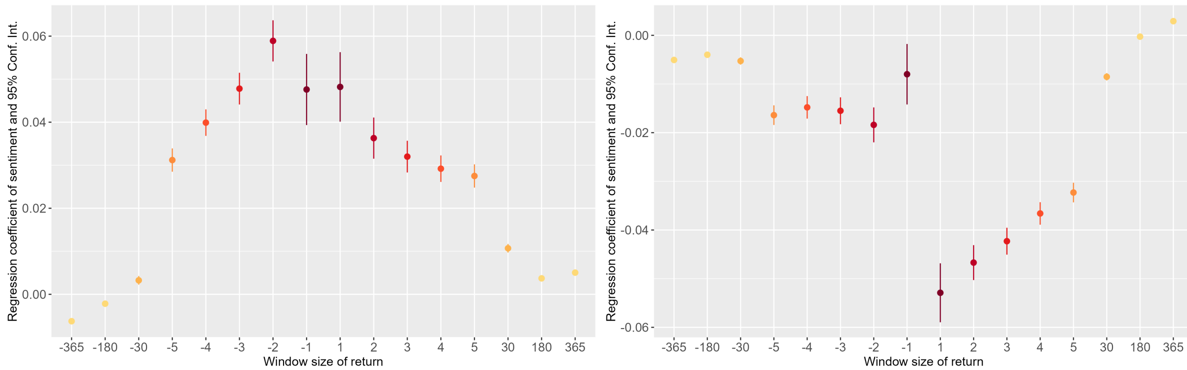
(B) Effect of negative sentiment

Figure 9. Effect of the probability of positive (panel [A]) and negative (panel [B]) sentiment of news articles about Japanese firms on percentage changes of their suppliers' stock prices for different time windows. When the value of the horizontal axis is negative and $-w$, the dot above the value indicates the point estimate of the pre-news effect for time window w (β_w^{pre}). When it is positive and w, the dot indicates the post-news effect for time window w (β_w^{post}). The color of the dots for time windows w and $-w$ is set to be the same so that the post- and pre-news effects can be easily compared. The confidence interval at the 5% level associated with each point estimate (dot) is shown by a vertical segment.

We further estimate the effect on clients and show the results in Figure 10. Compared with the previous results for firms across the world shown in Figure 7, we find that the three notable differences found in the effect on suppliers still hold in the effect on clients: (1) The average effect is generally larger for Japanese firms than for firms across the world; (2) The net effect of the disclosure of positive news about a firm on stock prices of its clients is negative; (3) The pre-news effect of negative news for the time window of 1 day is smaller than that for longer time windows.

In summary, we find that how positive and negative information about firms affect stock prices of their suppliers and clients before and after disclosure of the information by news medias is different between firms in Japan and in other countries. Although we cannot provide evidence of any mechanism behind the differences, one possible reason for this is the uniqueness of Japan's supply chains, known as *keiretsu*. Links between suppliers and clients in Japan's *keiretsu* are often stronger than those in other countries, because links in *keiretsu* are often associated with shareholding relationships, information exchanges, technical assistance, and research collaboration.[46,47] These strong relationships explain the larger effect of news about firms on their suppliers and clients. Because investors recognize the strength of ties and thus expect propagation of performance through supply chains, information about firms affect stock prices of their suppliers and clients more in Japan than in others.

Moreover, investors who can receive information about firms through private channels are more knowledgeable and recognize diffusion of performance through supply chains more accurately than other investors who rely on news medias. Therefore, once the knowledgeable investors receive positive information about a firm before its disclosure by news medias, they invest in the firm's suppliers and clients. This results in a large increase in stock prices of the suppliers and clients before the disclosure of news. However, other investors who rely on news medias and do not understand the role of supply chains react less to positive news after its disclosure.



(A) Effect of positive sentiment

(B) Effect of negative sentiment

Figure 10. Effect of the probability of positive (panel [A]) and negative (panel [B]) sentiment of news articles about Japanese firms on percentage changes of their clients' stock prices for different time windows. When the value of the horizontal axis is negative and $-w$, the dot above the value indicates the point estimate of the pre-news effect for time window w (β_w^{pre}). When it is positive and w, the dot indicates the post-news effect for time window w (β_w^{post}). The color of the dots for time windows w and $-w$ is set to be the same so that the post- and pre-news effects can be easily compared. The confidence interval at the 5% level associated with each point estimate (dot) is shown by a vertical segment.

5 Conclusion

This study examines how positive and negative news about firms affects the change rate of their stock prices and, moreover, how it affects the change rate of stock prices of the firms' suppliers and clients, using a large sample of publicly listed firms across the world and another of Japanese listed firms. The level of positiveness and negativeness of each news article is determined by FinBERT, a natural language processing model fine-tuned specifically for financial information. Supply chains of firms across the world are identified mostly by financial statements and supplemented by other information on the website and news medias, while those of Japanese firms are taken from large-scale firm-level surveys.

We find that positive news increases the change rate of stock prices of firms mentioned in the news before its disclosure, most likely because of diffusion of information through private channels, such as SNS and word of mouth. Positive news also raises stock prices of the firms' suppliers and clients before and after its disclosure, confirming propagation of market values through supply chains. In addition, we generally find a larger post-news effect on stock prices of the mentioned firms and their suppliers and clients than the pre-news effect. The positive difference between the post- and pre-news effects can be considered as the net effect of the disclosure of positive news, controlling for information diffusion through private channels. However, the post-news effect on suppliers and clients in Japan is smaller than the pre-news effect, a result opposite to those from firms across the world. This notable result is possibly because supply chain links of Japanese firms are stronger than global supply chains while such knowledge is restricted to selected investors.

The important opening question not addressed by this study is the significant heterogeneity of supply chain relationships, which can lead to varying impacts of news sentiment. For example, some suppliers are easily replaceable, while others are not; some trade relationships are long-term, potentially reflecting trust or sunk costs; additional links, such as shareholding or dual board membership, may exist; and the recognition of supply chain relationships by investors can vary. Examining the heterogeneity presents an important direction for future research.

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Acknowledgements

The authors thank Wataru Souma and Takayuki Yumoto for valuable discussions and Yuito Nishi for his technical contribution.

Author contributions statement

H.I conceived the study. H.I and Y.T conducted the analyses and wrote and reviewed the manuscript.