Quantifying News Tone to Analyze the Tokyo Stock Exchange with Deep Learning

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This paper studies the relationship between news and the Tokyo Stock Exchange (TSE) during 2003 to 2015. We employ recursive neural network, which is one of the form of deep learning, in order to quantify news tones from Reuters. Our three main findings are: news tones affect stock returns of the next trading day and receive impacts from stock returns of the previous trading day at the same time; the effect of news causes return reversals; the effect of news has a longer lasting and larger impact on small stock returns. These results are consistent with empirical analyses of the New York stock exchange. Our results also show that deep learning can quantify news tones better than the naïve Bayes classifier and the sentiment dictionary.

1. Introduction

In recent years, efforts have been under way to use unstructured data, such as images, voices and text information, for an analysis of asset prices. Unstructured data has not been commonly used previously because it is more difficult to handle unstructured data rather than structured data such as financial data, stock charts, and credit ratings. However, this unstructured data may contain information that is not reflected in structured data and it may be possible to acquire useful information that proves to be a source of excess return through an analysis of unstructured data. This research made an attempt to analyze unstructured data by focusing particularly on text information in the form of news articles.

As preceding studies on the asset price analysis using text information, for example, Antweiler and Frank [2004], while noting that postings on the Internet bulletin board do not have the predictability of stock prices, reported that an increase in the number of postings offers the possibility of predicting a rise in the volatility of stock prices. Tetlock [2007] estimated the degree of pessimism in *The Wall Street Journal* columns and found a connection between the degree of pessimism and the Dow Jones Industrial Average, concluding that news articles contain not only information on fundamentals but also information on market sentiments. Tetlock *et al*. [2008] also analyzed *The Wall Street Journal* and Dow Jones News Service in terms of individual companies and found that it is possible to predict their stock prices and corporate earnings in the future on the basis of the analysis. These results suggest that news articles contain information on fundamentals and it is reflected in stock prices immediately.

Furthermore, there are study reports that refer to the relevance of text information not only to asset prices but also to investor behaviors on the financial market. Engelberg *et al*. [2012] make an analysis of the Dow Jones Market News and notes that the number of short sellers increases after the distribution of news articles, suggesting that investors do not trade in anticipation of news but gain excess return with the superior ability of processing and responding to news. The study also reports that by the use of negative news, it is possible to obtain a cumulative return of as much as 180% during a two and a half year period. Dougal *et al*. [2012] examined *The Wall Street Journal* columns to extract the characteristics of texts and sentences by the journalists who wrote them and found the connection between them and the stock market, reporting that journalists have a large impact on investor behaviors. Among other preceding studies, Garcia [2013] analyzed *The New York Times* articles from 1905 to 2005 and noted that investor sentiments have a significant influence on the stock market in tough economic times since the news content is useful for predicting stock prices during recessions.

There are similar research reports on the Japanese securities market. Maruyama *et al.* [2008] analyzed the postings on the Yahoo! Finance bulletin board and found that the number of postings is a leading indicator of market volatility and trading volume. Jotaki *et al*. [2009] made an analysis with a focus on credit and found a strong connection between corporate bonds with low credit ratings and news articles. Okada and Hamuro [2011] classified news articles distributed by Bloomberg into optimistic, neutral and pessimistic categories. They reported that the market sentiment index developed on the basis of the news categorization is negatively correlated with market volatility with the sentiment index leading the volatility. Goshima and Takahashi [2016] found the connection between corporate social responsibility (CSR) activities and stock prices through mining the text in Nikkei QUICK news articles. Recently, textual analysis has been used in the area of accounting as well (Allee and DeAngelis [2015]).

While a variety of analyses have been conducted using text information, there are studies that came up with different conclusions from others. Okimoto and Hirasawa [2014] analyzed news articles using the same validation model as Tetlock [2007] and reported that news articles only have fundamental information, reaching a different conclusion than Tetlock [2007]. One of the factors this behind differing conclusion may have to do with the accuracy of positive and negative information estimates contained in news articles.

With respect to this problem, it may be possible to analyze a more elaborate connection between news articles and the market with the use of deep learning, which has been in the spotlight in recent years as a breakthrough in the artificial intelligence field. It has been found that deep learning makes it possible for computers to automatically extract a feature quantity from unstructured data, a job that has previously been done manually, and it is also possible to extract a more accurate feature quantity (Hinton *et al*. [2006]). In addition, textual analysis' higher performance than the conventional method has been reported with the application of deep learning (Socher *et al*. [2013]). Therefore, this research conducted a sentiment analysis of news articles by deep learning focusing on text information of news articles and attempted to analyze the connection between the sentiment analysis and stock prices. We will discuss data to be used in this analysis in Chapter 2, the method of analysis in Chapter 3 and the results of the analysis in Chapter 4, with the conclusions described in Chapter 5.

2. Data

(1) Market Data

As for the market data, we used the TOPIX stock price index and volume of the First Section of the Tokyo Stock Exchange (TSE) from Thomson Reuters Datastream. We also used daily data of the size factor return (SMB = Small Minus Big) from the Japanese version of the Fama-French benchmarks provided by Financial Data Solutions, Inc.

(2) News Data

We used Reuters News for news data. Reuters News is the news distributed by Thomson Reuters, one of the world's most-widely known news services. This research's analysis covers the English news articles related to the Tokyo Stock Exchange and used the texts of the news articles. We used the time and date of the distribution of the news articles for the tag information.

The text information used for textual analysis is broadly classified into the three categories of information provided by individual companies, information distributed by media and the postings on the Internet (Kearney and Liu [2014]). Among news articles provided by companies are financial statements and earnings statements by management and annual reports. News articles distributed by the media include newspaper and magazine articles, and specialized news items provided by Reuters, Nikkei QUICK and others. Postings on the Internet includes postings from the Yahoo! Finance bulletin board and Ranking Bull, etc.

Reuters News is categorized as information distributed by the media. Compared with primary information distributed by each organization involved, information distributed by the media is the product of selection by reporters working for media organizations and analysts and is thought to contain relatively important information for society and the market. Reuters News is the media that is viewed by a lot of investors participating in the Japanese securities markets and is characterized by relatively small time lags between the occurrence of an event and the distribution of relevant news in comparison with news provided by newspapers and television. The period covered by the analysis is between January 1, 2003, and May 31, 2015. We made the analysis by using all of the English Reuters News articles related to the Tokyo Stock Exchange distributed during that period.

3. Methods

(1) Development of News Indexes

In this research, we developed a news index by deep learning and, for the purpose of comparison, we also developed news indexes using the naive Bayes classifier, the representative conventional method, and Loughran and McDonald Financial Sentiment Dictionaries (hereinafter referred to as "LM Dictionaries"). For the development of the news indexes, we used Tetlock *et al*. [2008] and Loughran and McDonald [2011] as references. We describe the details of the methods for developing the indexes below.

(2) Pre-Processing

Let us describe data fairing before the carrying out the analysis. In the analysis of this research, we proceeded with the analysis by incorporating news articles distributed at 3pm or later into those of the following business day and similarly incorporated news articles distributed during market holidays into those of the next business day. We took this approach by assuming that the content of news articles distributed while the market is closed is reflected in the prices on the following business day. Next, as we tabulated positive expressions and negative expressions in units of the sentence, we extracted sentences from news articles made up of more than two sentences [(Note1)]. After a string of these processes, the number of sentences came to 990,628.

(3) Methods of Developing the News Indexes by Deep Learning and the Naive Bayes Classifier

We classified all the respective news article sentences into positive and negative expressions by using deep learning and the naive Bayes classifier.

We used the Recursive Neural Network as the deep learning model for this research. This is a model that calculates the vectors of phrases (sentences) recursively depending on the phrase structure and one of the deep learning models reported to have high performance in the sentiment analysis of text data. As sentences are expressed in fixed-length vectors through the

[(Note 1)] The extraction of sentences is programmed under certain rules. In this analysis, we extracted only texts that include complete sentences in accordance with English grammar as our analysis covered text information.

composition of word vectors according to the form of syntactic trees using the neural network after the syntactic tree analysis of documents, it becomes possible to obtain vectors that take sentence structures into account. Furthermore, we used the recursive neural tensor network (Note2) proposed by Socher *et al*. [2013], which is noted for its high classification accuracy.

The naive Bayes classifier is one of machine learning methods widely used in the text classification analysis. Since it is the probabilistic classifier based on Bayes' theorem and often regarded as a benchmark in the natural language processing field, we referred to it for comparison in this analysis (Okumura and Takamura [2010]) (Note3).

For training data in this analysis, we used the document data consisting of 11,855 sentences used in Socher *et al*. [2013] (Note4). For classification class, we classified the data into the five classes of “Very Negative,” “Negative,” “Neutral,” “Positive” and “Very Positive.”

Next, we developed scores by tallying the sentences classified according to each business day for each class, multiplying the number of the sentences for each class by negative 1 for “Negative” and by negative 2 for “Very Negative,” and then dividing them by the number of sentences other than the sentences classified as “Neutral.” Tetlock *et al*. [2008] quantified the pessimism degree of news articles by counting negative words only because of the weak explanatory power of positive words. In this research, we follow the practice of the preceding study and quantified the news articles by counting negative sentences only. More specifically, the score is expressed by the following formula:

$$Score_t = \frac{-N - 2VN}{VP + P + N + VN}$$

VP represents the number of sentences classified as “Very Positive,” *P* represents the

(Note 2) As the activation function, the hyperbolic tangent function is used for the hidden layer and the softmax function for the output layer.

(Note 3) In this research, in order to solve the zero frequency or sparseness problem with the naive Bayes classifier where documents containing words that do not exist in the training data, we conducted Laplace smoothing by adding one to the frequency of appearance of any word in advance. It means that we adopted the Dirichlet distribution of α = 2 as the prior probability distribution.

(Note 4) In this research, we use general documents, instead of documents in the financial sector, as the training data. Tetlock [2007] and Tetlock *et al*. [2008] use commonly-used dictionaries defined by psychologists for the positive/negative estimates of news articles, and we follow this practice in this research. However, as there are study reports that unique vocabularies tend to be used in the financial sector, an analysis that uses some of news articles as the teacher information is an issue that has to be dealt with in the future. Document data and label data are available at http://nlp.stanford.edu/sentiment/.

number of sentences classified as “Positive,” *VN* the number of sentences classified as “Very Negative,” and *N* the number of sentences classified as “Negative,” respectively. Here, we standardized the scores for each business day using the overall scores, as done in Tetlock [2007].

$$Index_t = \frac{Score_t - \mu_{Score}}{\sigma_{Score}}$$

We developed the news indexes using the above procedures and made the analysis.

(4) Methods of Developing the News Index with the LM Dictionaries

In this section, we describe the development of the news index based on the LM Dictionaries in detail. The LM Dictionaries are the word lists used in Loughran and McDonald [2011] (Note5) and the dictionaries widely used in the analysis of English texts in the financial sector. In the LM Dictionaries, 354 positive words and 2,355 negative words respectively are defined.

Based on the LM Dictionaries, we counted the words in the news articles and calculated the scores by dividing the value obtained by multiplying the number of negative words by negative 1 the number of words counted. More specifically, the score is expressed by the following formula:

$$Score_t = \frac{-N}{P + N}$$

P and *N* represent the positive words and negative words, respectively, defined in the LM Dictionaries. We calculated and then standardized the scores for each business day by similarly using the overall scores.

$$Index_t = \frac{Score_t - \mu_{Score}}{\sigma_{Score}}$$

We developed the news index using the above procedures and made the analysis.

(Note 5) The word lists are available at http://www3.nd.edu/~mcdonald/Word_Lists.html.

(5) Amount of Basic Statistics of the News Indexes

Figure 1 summarizes the amount of basic statistics of the news indexes developed by using the procedures described above.

IndexDL represents the news index developed by using deep learning, IndexNB the news index developed by using the naive Bayes classifier, and IndexLM the news index developed by using the LM Dictionaries (Note6).

The sample size of the news indexes is a total of 3,043 business days from January 2003 to March 2015. The autocorrelation coefficient (1), which represents the primary autocorrelation coefficient, is 0.18 for IndexDL, 0.33 for IndexNB and 0.45 for IndexLM, respectively, at a significance level of 1%. IndexDL has a statistically significant value but the level itself is relatively low. On the other hand, IndexNB and IndexLM have a weak autocorrelation. The autocorrelation between the news indexes represents the coefficient of correlation with IndexDL, and is 0.28 for IndexNB and 0.21 for IndexLM, respectively, at a significance level of 1%. There is a certain correlation between the news indexes but the level of correlation is relatively low.

(Note 6) Regarding the methodological differences, the LM Dictionaries (positive/negative dictionaries) is the method to calculate the positive/negative words by counting the words in sentences based on the words list defined manually in advance, while the naive Bayes classifier and deep learning are the methods to calculate the positive/negative words and sentences from the teacher data based on the statistical nature. Of the latter two, deep learning is assumed to be capable of making a more accurate analysis as it is the text-mining method that takes the structure of sentences into account as well.

Figure 1 Amount of Basic Statistics of the News Indexes

	IndexDL	IndexNB	IndexLM
Sample size	3,043	3,043	3,043
Average	0	0	0
Standard deviation	1	1	1
First quartile	-0.62	-0.63	-0.72
Second quartile	-0.05	-0.02	-0.01
Third quartile	0.52	0.61	0.70
Autocorrelation coefficient(1)	0.18 ***	0.33 ***	0.45 ***
Correlation between the news indexes		0.28 ***	0.21 ***

Note: IndexDL represents the news index developed by using deep learning, IndexNB the news index developed by using the naive Bayes classifier and the IndexLM the news index developed by using the LM Dictionaries. ***, ** and * show that the value is statistically significant at the significance level of 1%, the significance level of 5% and the significance level of 10%, respectively.

Source: Prepared by the authors. The same is applicable below.

(6) Analysis of the News Indexes by the VAR Model

We made the analysis based on the news indexes developed in the preceding section. The method of analysis follows the methods of Tetlock [2007] and Okimoto and Hirasawa [2014], who made similar analyses of the Japanese stock market. More specifically, we proceeded with the analysis of information contained in news articles by the following four Value-at-Risk (VAR) models (Note7), based on the three hypotheses of the information theory, sentiment theory, and the no-information theory.

(Note 7) Okimoto and Hirasawa [2014] did not examine the impact on small-capital stocks, but Tetlock [2007] considered that impact. So, this research also covered the impact on small-capital stocks.

$$Tpx_t = \alpha_1 + \sum_{j=1}^{5} \beta_{1j} Tpx_{t-j} + \sum_{j=1}^{5} \gamma_{1j} Index_{t-j} + \sum_{j=1}^{5} \delta_{1j} Vol_{t-j} + \varepsilon_{1t} \quad (1)$$

$$Index_t = \alpha_2 + \sum_{j=1}^{5} \beta_{2j} Tpx_{t-j} + \sum_{j=1}^{5} \gamma_{2j} Index_{t-j} + \sum_{j=1}^{5} \delta_{2j} Vol_{t-j} + \varepsilon_{2t} \quad (2)$$

$$Vol_t = \alpha_3 + \sum_{j=1}^{5} \beta_{3j} Tpx_{t-j} + \sum_{j=1}^{5} \gamma_{3j} Index_{t-j} + \sum_{j=1}^{5} \delta_{3j} Vol_{t-j} + \sum_{j=1}^{5} \psi_{3j} |Index_{t-j}| + \varepsilon_{3t} \quad (3)$$

$$SMB_t = \alpha_4 + \sum_{j=1}^{5} \beta_{4j} Tpx_{t-j} + \sum_{j=1}^{5} \gamma_{4j} Index_{t-j} + \sum_{j=1}^{5} \delta_{4j} Vol_{t-j} + \varepsilon_{4t} \quad (4)$$

Tpx represents the daily logarithmic return (%) of TOPIX, *Index* the news, *Vol* the logarithmic value of the daily volume of the TSE first section, and *SMB* the size factor return, respectively. The order is 5 because it is assumed that it is influenced by the daily return of TOPIX, volume and the news indexes of the past 5 business days.

4. Results

(1) The Impact of the News Indexes on Stock Returns

First, we considered the impact of the news indexes on the TOPIX return based on the results of Formula (1). What is important to note here is that if γ_{1j} in Formula (1), due to either of *j*, turns positive and then turns negative, it means that the impact of news on the stock market includes a transient one and the news contains not only information on the fundamentals but also information on the sentiments. If the positive impact remains intact, however, it means that the news contains only information on fundamentals. In addition, in the case where γ_{1j} does not turn either positive or negative and has no impact on the stock market, it means that the news has no information whatsoever. On the basis of the above, we examined the results of the analysis. **Figure 2** summarizes γ_{1j} in Formula (1). IndexDP represents the news index developed by using deep learning, IndexNB the news index developed by using the naive Bayes classifier and the IndexLM the news index developed by using the LM Dictionaries, and the figure summarizes value t calculated respectively by using γ_{1j} estimated by Formula (1) and Newey-West standard errors.

Based on the analysis results, it was observed that with the IndexDL, γ_{11} is 0.070 at a significance level of 1% and the news index had a positive impact on stock returns on the following business day. Also, as γ_{14} stands at −0.062 at the significance level of 10%, stock prices rebounded with a lag of the four business days, with a return reversal observed. This means that although the news index does influence the stock market, the impact of the news includes a transient one and the news contains not only information on the fundamentals but also information on the sentiments. With IndexLM as well, as γ_{11} stood at 0.049 at a significance level of 10% and γ_{15} also came to −0.052 at a significance level of 10%, a similar trend was observed. These results present a sharp contract with Okimoto and Hirasawa [2014], who showed that a return reversal was not observed and that the news index contains no information on sentiments, but are consistent with the results of Tetlock [2007], which showed that a return reversal was observed and that the news index does have information on sentiments. Furthermore, Tetlock [2007] that analyzed the U.S. stock market reported that the significant return reversal was observed after the four business days, it is one of the interesting results that this research, which covered the Japanese stock market, also observed the significant return reversal after the same four business days. However, for IndexNB, none of γ_{1j} showed the statistically significant results. While the naive Bayes classifier is easy to handle, it makes an analysis under the strong assumptions, such as the independence of the appearance of words. Thus, it may be possible that an adequate accuracy is not ensured (Note8).

(Note 8) Basic research has produced reports that the use of deep learning enables the sentiment analysis with a higher accuracy than conventional methods. This research may have obtained the results with a relatively high accuracy with the use of deep learning. A detailed analysis remains an issue to be dealt with in the future.

Figure 2 Impacts of the News Indexes on TOPIX Returns

γ_{1j}	IndexDL			IndexNB		IndexLM		
γ_{11}	0.070	***	(3.122)	0.003	(0.125)	0.049	*	(1.794)
γ_{12}	-0.047		(-1.563)	0.044	(1.639)	0.006		(0.200)
γ_{13}	-0.012		(-0.455)	-0.004	(-0.161)	0.000		(0.002)
γ_{14}	-0.062	*	(-1.771)	-0.002	(-0.080)	-0.008		(-0.282)
γ_{15}	0.006		(0.248)	0.004	(0.163)	-0.052	*	(-1.881)

Note: This table summarizes the values estimated by the VAR models using the news indexes and the daily logarithmic returns of TOPIX during the 3,043 business days from January 2003 to May 2015. ***, ** and * show that the value is statistically significant at a significance level of 1%, a significance level of 5% and a significance level of 10%, respectively. Figures in the parentheses show value *t* calculated for error terms by using Newey-West standard errors that is robust to heteroskedasticity and autocorrelation up to five lags. The same is applicable below.

(2) Impacts of Stock Returns on the News Indexes

Next, we considered the impact of TOPIX returns on the news indexes. Here, the value of β_{2j} in Formula (2) becomes important. If the news reacts only to movements of the stock markets, β_{2j} is positive with any value of j, and this means that the news is reacting by following the market. On the other hand, if β_{2j} is not significant, it means that there is no connection between the stock market movements in the past and the news. We interpreted the results of the analysis based on these developments. **Figure 3** summarizes value t calculated by using β_{2j} estimated by Formula (2) and Newey-West standard errors.

Based on the analysis results, it was observed that with the IndexDL, β_{2j} is 0.024 at a significance level of 10% and this means that the news index is reacting by following the TOPIX return on the preceding business day. In other words, this suggests the existence of descriptions of the market conditions on the preceding business day in the news [Note9]. These results are consistent with Tetlock [2007], but not consistent with Okimoto and Hirasawa [2014]. For IndexLM, the sign of β_{21} is positive to show a trend similar to IndexDL, but the statistically

[Note 9] There are news articles that describe the market conditions in the past, and they can be considered consistent with the analysis results of this research. A detailed analysis remains an issue to be dealt with in the future.

significant results could not be obtained. The statistically significant value of β_{2j} was not obtained for IndexNB, either. These results indicate the possibility of being able to obtain the results that are difficult to obtain with the conventional methods by using a new method. A detailed analysis remains an issue to be dealt with in the future.

Figure 3 Impacts of the TOPIX Returns on the News Indexes

β_{2j}	IndexDL		IndexNB		IndexLM	
β_{21}	0.024 *	(1.659)	-0.003	(-0.295)	0.007	(0.674)
β_{22}	0.005	(0.476)	-0.012	(-0.993)	-0.004	(-0.324)
β_{23}	-0.012	(-0.600)	-0.010	(-0.745)	-0.003	(-0.279)
β_{24}	0.012	(1.000)	0.004	(0.343)	0.003	(0.323)
β_{25}	0.002	(0.124)	0.000	(0.023)	-0.008	(-0.726)

(3) Impacts of the News Indexes on Volume

Thirdly, we considered the impact of the news indexes on volume. Here, the values of γ_{3j} and ψ_{3j} in Formula (3) are important. Coval and Shumway [2001] and Antweiler and Frank [2004] referred to the connection between media and trading costs/liquidity/volume. In Formula (3) similarly, if *Indext-j* serves as the surrogate variable of trading costs, it should become positive with either of γ_{3j} and when the news index becomes smaller, it should have the impact of reducing volume. On the other hand, if $|Index_{t-j}|$ in Formula (3) becomes the surrogate variable of investor sentiments, it should become positive with either of ψ_{3j}, and when the absolute value of the news index becomes larger, it should have an impact of increasing volume. These arguments are based on the theories of Campbell *et al*. [1993] and DeLong *et al*. [1990] that when the divergence of the sentiments from the average grows larger, liquidity-based traders buy and sell stocks and market makers conduct trading in response to them, trading volume expands. We interpreted the results of the analysis based on these developments. **Figure 4** summarizes value *t* calculated by using γ_{3j} and ψ_{3j} estimated by Formula (3) and Newey-West standard errors.

Based on the analysis results, for IndexDL, while γ_{34} comes to 0.008 with a significance level of 10%, γ_{31} does not have any significant value, showing no impact on the following business day. This shows that they do not serve as the surrogate variable of trading costs. On the other hand, as ψ_{31} stands at 0.009 at a significance level of 10% to mean that the absolute value of the news index has an impact on volume, indicating the possibility that it serves as the surrogate variable of the sentiments. Here as well, the analysis results were consistent with Tetlock [2007]. However, with respect to the other news indexes, while γ_{31} has a significant value for IndexNB, indicating the possibility of it serving as the surrogate variable of trading costs, ψ_{31} does not show any significant value, indicating the possibility of it not serving as the surrogate variable of sentiments. An analysis with a more appropriate surrogate variable is an issue to be dealt with in the future.

Figure 4 Impacts of the News Indexes on Volumes

γ_{3j}	IndexDL		IndexNB		IndexLM	
γ_{31}	-0.005	(-1.158)	0.011 ***	(2.705)	-0.003	(-0.528)
γ_{32}	0.006	(1.275)	0.000	(-0.107)	-0.004	(-0.966)
γ_{33}	0.003	(0.687)	0.006	(1.232)	0.004	(0.843)
γ_{34}	0.008 *	(1.957)	-0.007 *	(-1.834)	-0.007	(-1.525)
γ_{35}	-0.001	(-0.338)	0.000	(0.028)	0.011 **	(2.314)

ψ_{3j}	IndexDL		IndexNB		IndexLM	
ψ_{31}	0.009 *	(1.710)	-0.002	(-0.336)	-0.010	(-1.375)
ψ_{32}	0.001	(0.215)	-0.008	(-1.138)	0.011	(1.596)
ψ_{33}	0.004	(0.688)	0.003	(0.425)	0.008	(1.312)
ψ_{34}	0.001	(0.274)	0.013 **	(2.362)	0.002	(0.300)
ψ_{35}	0.011 *	(1.914)	0.007	(1.123)	-0.001	(-0.135)

(4) Impacts of the News Indexes on Small-Capital Stocks

Finally, we examined the impact of the news indexes on small-capital stocks. Here, the value ofγ_{4j} in Formula (4) becomes important. Companies with smaller market capitalization have the characteristics of being influenced by individual investors to a relatively large extent and it may be more difficult to obtain information from them. Thus, the influence of news on small-capital stocks may be different from that on large-capital stocks. If γ_{4j} has a statistically significant value, it means that the news indexes do have an impact on small-capital stocks, apart from the prediction power on TOPIX returns. We interpreted the results of the analysis based on these developments. **Figure 5** summarizes value t calculated by using γ_{4j} estimated by Formula (4) and Newey-West standard errors.

Based on the analysis results, for IndexDL, γ_{42} is 0.025 at a significance level of 5% and γ_{43} is 0.032 at a significance level of 1%, showing that the news indexes is giving an impact on small-capital stocks, apart from the prediction power on TOPIX returns. Positive values of γ_{42} and γ_{43} mean that the impact of the news indexes on small-capital stocks is relatively large and sustained. In particularly, the fact that the news indexes are having an impact on SMB the two business days and also the three business days later indicates that the information contained in the news are being gradually reflected in prices of small-capital stocks. As Tetlock [2007] also referred to the impact on SMB the four business days later, this research observed a similar trend. On the other hand, γ_{4j} does not show any statistically significant value for IndexNB or Index LM. It is interesting to note that the analysis results that are difficult to find with the conventional methods (IndexNB and IndexLM) were obtained through the new method (IndexDL). A detailed analysis remains an issue to be dealt with in the future.

Figure 5 Impacts of the News Indexes on SMB

γ_{4j}	IndexDL		IndexNB		IndexLM	
γ_{41}	-0.020	(-1.644)	0.009	(0.731)	0.003	(0.202)
γ_{42}	0.025 **	(2.352)	-0.006	(-0.479)	-0.013	(-1.066)
γ_{43}	0.032 ***	(2.693)	0.002	(0.184)	0.006	(0.454)
γ_{44}	0.015	(1.249)	-0.008	(-0.700)	0.008	(0.603)
γ_{45}	0.010	(0.693)	-0.007	(-0.513)	0.005	(0.403)

5. Conclusions

This research focused on the text information of the news articles, made a sentiment analysis of the news articles by deep learning, in contrast to the conventional methods, and analyzed its connection with stock prices. As a result of the analyses, we reached the conclusions that the news indexes do have an impact on the market of the next trading day, in addition they are likely to react by following the market movements, that the return reversal observed suggests the possibility of the news indexes having information on market sentiments, and that the impact of the news indexes on small-capital stocks is relatively large and sustained [Note10]. One of the features of this article is that using the new method indicated the possibility of the news indexes causing the return reversal and following the stock markets on the Tokyo Stock Exchange.

As the analysis of textual data is considered to be susceptible to large errors relative to the analysis of numerical data, an analysis with a more appropriate method is an issue to be dealt with in the future. The future challenges also include an analysis of the securities markets of other countries and media, the application to securities investment and the consideration of the impact of the news indexes on stock prices on the same trading day.

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[Note 10] These results are consistent with the results of the preceding studies that analyzed the U.S. stock market.

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