Time Series Analysis of Thai Flooding Effects on Japanese Insurance Companies

Yuriko Yano, Department of Management, Faculty of Economics,
Gakushuin University, Japan
Yukari Shirota, Department of Management, Faculty of Economics,
Gakushuin University, Japan

The IAFOR International Conference on the Social Sciences – Hawaii 2017
Official Conference Proceedings

Abstract
In this paper, we analyzed effects of the 2011 Thai flooding on Japanese economics. In the paper, we propose, as a new time series economics data analysis method, an integrated approach of Singular Value Decomposition on stock data and news article text mining. There we first find the correlations among companies' stock data and then in order to find the latent logical reasons of the associations, we conduct text mining. The paper shows the two-stage approach's advantages to refine the logical reasoning. Concerning the Thai flooding effects on the Japan's economy, as unexpected moves, we have found the serious harms on the Japanese insurance companies, especially SOMPO Japan even though the Thai flood did not occur in Japan.

Keywords: Time Series Analysis, Random Matrix Theory, Japanese Insurance Companies, Thai

Introduction

In this paper, we will analyze effects of the 2011 Thai flooding on Japanese economics. Many Japanese companies were devastated by the floods. To analyze the damages, we use Singular Value Decomposition (SVD) on stock data to find the correlations among companies' stock data. The approach is called the random matrix theory in the financial field. As the stock price data, we used Nikkei 225 that expresses the Japanese major companies' economical climates. The target period is from September to December in 2011. In 2011, the Japan economy was severely damaged by the great East Japan earthquake that happened on 11th March. To pay the insurance premium, Japan major insurance companies were also damaged. In addition, the flood in Thai in the beginning of the October also attacked the Japanese economy. In the paper, we focus on the time series changes of the insurance companies after the Thai flooding.

In the next section, we shall explain a random matrix theory. In the section "Time Series Stock Data Analysis", we describe the result of the SVD. The data used is the Nikkei 225 during three months from October to December 2011. In the section "Cause and Effect Relationship between Japanese Insurance Companies and the Thai Flood", we would like to reveal the cause and effect relationship between Japanese insurance companies and the Thai flood from the result of the SVD. Then in the section "Time Series Movement of Effects", we evaluate the time series movement of damage effect. Finally, we conclude the paper.

Random Matrix Theory

In the section, we will explain our methods. Our final research objective is measurement of natural disaster effects on Japan's economy conditions. The disasters include Japan's earthquakes and other countries' earthquakes and floods. In the methods, first we analyze Japan's stock price data such as Nikkei 225. The analysis method we adopted is Singular Value Decomposition (SVD) (B. Efron, 2010, C. M. Bishop, 2006). The SVD is used in various kinds of applications; For example, in text mining, LSA (Latent Semantic Analysis) uses the SVD. Concerning the SVD math process, Shirota et al. visually explained the intrinsic meanings (Y. Shirota, and B. Chakraborty, 2015, Y. Shirota, and B. Chakraborty, 2016).

We conduct the SVD on the standardized return values of stock price data. The return value is defined to be the ratio between today's price and the previous day's one and defined as follows: $G_{i,j} = \ln(S_{i,j}/S_{i,j-1})$ where $S_{i,j}$ is the i-th company's stock price on j-th day and $G_{i,j}$ is the return value on j-th day.

In the stock data analysis, each company's data during the period is standardized, so the mean value becomes 0 and the standard deviation becomes 1. Because different stock values have varying levels of variance, the return value must be standardized. In our previous researches on the Thai 2011 flooding effects, we had found the damaged industry classes by using the SVD methods (M. F. Lubis, Y. Shirota, and R. F. Sari, 2015, M. F. Lubis et al, 2015). The SVD is a kind of Principal Component Analysis (PCA). Mathematically, from SVD, we can obtain two kinds of eigenvectors (principal components). In this analysis, we call them (1) Brand-Eigenvector and (2)

Dailymotion-eigenvector. The Brand-eigenvector identifies similar movement companies. The Dailymotion-Eigenvector covers the class's average time series fluctuation.

By the flooding, many Japan-affiliated companies in Thai were damaged. The damaged products included hard disk drives, electric parts of automobiles, food and beverages, and digital cameras (S. Sukegawa, 2013, P. Cooke, 2013). To find the damaged company class, we used the well-known fact that Japanese digital camera company Nikon was severely devastated. We searched Nikon as the mark to find the damaged Japanese company Brand-Eigenvectors. The element value of each company may be positive or negative. Its positive/negative is only up to the eigenvector direction. The damaged company element may be positive. If a principal component has many damaged companies with large element values, the principal component can be interpreted as the damaged class.

In general, the SVD method is, in a financial analysis, called the random matrix approach and it is utilized to find the stable company classes (M. Potters, J.-P. Bouchaud, and L. Laloux, 2005, G. W. Anderson, A. Guionnet, and O. Zeitouni, 2009, J.-P. Bouchaud, and M. Potters, 2011). Using the extracted stable classes, they make a high performance portfolio (V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, and H. E. Stanley, 2000, V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, T. Guhr, and H. E. Stanley, n.d.). Our usage of eigenvalues and eigenvectors in the SVD is identical to one by Plerou's proposed cross correlation analysis (G. W. Anderson et al, 2009, J.-P. Bouchaud et al, 2011). The conversion method between both was described in our paper (M. F. Lubis et al, 2015). Our research goal is, however, completely different from theirs and we would like to find the time series effects of the disaster on stock prices. A disaster triggers a stock downfall and one industry's breakdown inflicts harm and transmit on others like a supply chain breakdown. The effects are dynamic and not stable; some industries will recover soon and the damage will instantly diminish and others are not. We would like to investigate the time series changes from a viewpoint of time series data analysis. In other words, we are interested in the effect duration period and its magnitude.

Time Series Stock Data Analysis

In the section, we describe the result of the SVD. The data used is the Nikkei 225 during three months from October to December 2011. We have conducted SVD on each month. The matrix size on each month is 225 (companies) times 20 (days). Therefore, we can obtain 20= Min (225, 20) principal components each month. Among the Oct. 20 principal components, we did select #2, #3, #5, #6, #7, #8, and #13 as the damaged classes. The October was the most severely damaged month. Fig.1 shows the selected five damaged Brand-Eigenvectors and their damaged industry names in October. The selection criteria is 1.2 there. The industry elements with bigger than 1.2 are extracted and drawn there. The edge length has no meaning in the graph. In Fig.2, the original Japanese industry names are written in Japanese, and only key company names are written in English such as NIKON and AJINOMOTO. The class, #3, can be interpreted as a food and drink industry class because they include AJINOMOTO, KIKKOMAN, MEIJI, KIRIN, and ASAHI. The #5 class include many financial industries such as Bank of YOKOHAMA, Bank of

SHIZUOKA, Bank of CHIBA, RESONA (bank), and SOMPO JAPAN. The #7 class include many spinning/textile companies such as TORAY, TEIJIN.

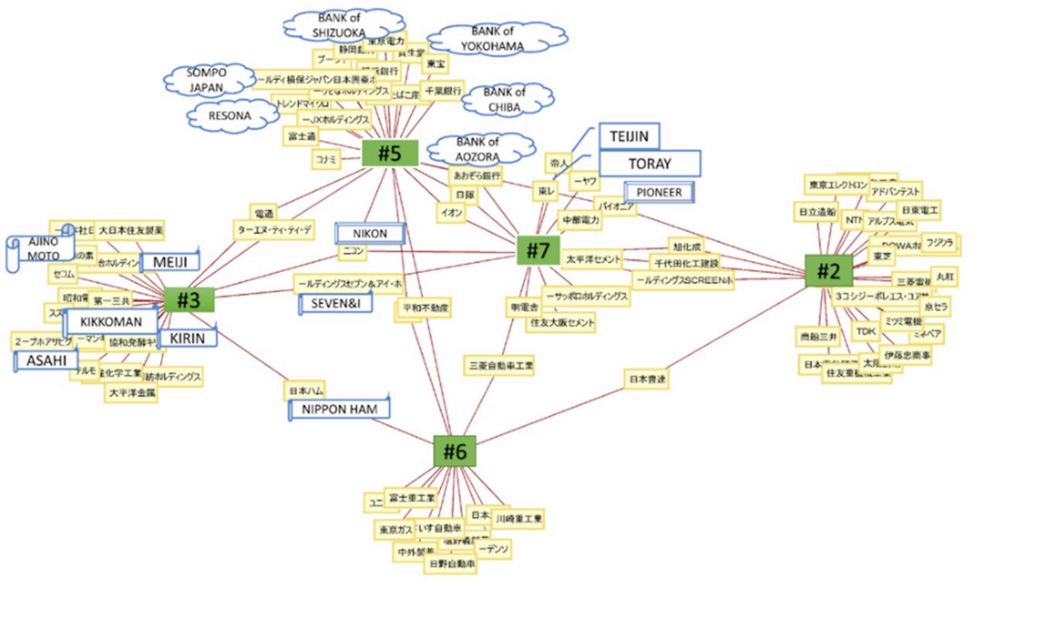

Figure 1: The damaged Brand-Eigenvectors #2, #3, #5, #6, and #7 and the damaged industry names.

Let us consider the time series change on the classes. Fig. 2 shows monthly movements on the numbers of the extracted industries with bigger than 1.2 values. For example, the number of #3 has changed as 20 – 28 – 21. Fig. 4 also shows the time series changes that focuses on the eigenvalue magnitudes. The eigenvalues express the class effect impact; the bigger it is, the more harms exist. Among classes, we can see the class integrations and divisions. In October and November, # 2 could be interpreted as an electronics industry class, from the member lists. As the both values in Fig. 2 and 3 are the biggest among the classes, we can interpret that the class was the most damaged class. This is consistent with the fact that the electronics companies had severely damaged. However, in December, the electronics industry category has been divided into #5, #7, and #8. It is possible to assume that the electronics industry had many damages, and we can guess that they consumed a plenty of time to recover from the damages. The damages must have prolonged; therefore, the class was divided to three classes depending on the damage recovery features.

On the other hand, the drink and food industry must have been recovered quickly. In October, #3 could be interpreted as a food and drink industry class. The eigenvalue of #3 in Fig. 4 October data, 14.2, is the second largest one in October; however, in November, there is no food and drink industry anymore, and in December, we can find a few beverage companies in #13. The ratio is the smallest in the month. It means that food and drink industry recovered from the flood more quickly than electronics industry.

Spinning industry also does change. In October, spinning industry class is #7 (the eigenvalue is 12.2), and it changes into #3 in November (See Fig. 3). After the month, the class number is stable as #3. Absolutely, spinning industry was suffering from the flood for a while because their factories were flooded. For instance, TORAY is a maker of fibers, textiles, resins, plastics, films, chemicals, ceramics, composite materials, medical products, and electronics, according to its official website, and this company has some factories in Thailand. TTS, Thai Toray Synthetics, has three factories in Bangkok, Ayutthaya, and Nakhon Pathom. TTTM, Thai Toray Textile Mills, has one factory in Nakhon Pathom, too.

The factory in Ayutthaya had the worst damages, and it needed more time to operate the factory. However, the others started to resume their operation in the year. In addition, Toray carried out alternative production immediately using its global networks. Toray could manage and make a quick recovery from the flood; hence, Toray did not have as terrible troubles as an electronics industry. It is quite possible to assume that other spinning companies had the similar actions, and as a result, spinning industry itself was not as a seriously damaged industry as an electronics industry.

Let us consider the financial industry class. The class, #5, in October can be interpreted as a financial industry, and there are lots of Japanese general insurance companies in the class. These companies themselves did not have physical direct damages. Nonetheless, the level of damage is the third largest in October. The reason must be that there were bunches of Japanese companies in Thailand and that the insurance companies had a huge amount of insurance expenses of them. Later, we could confirm the cause and effect relationship by conducting SVD.

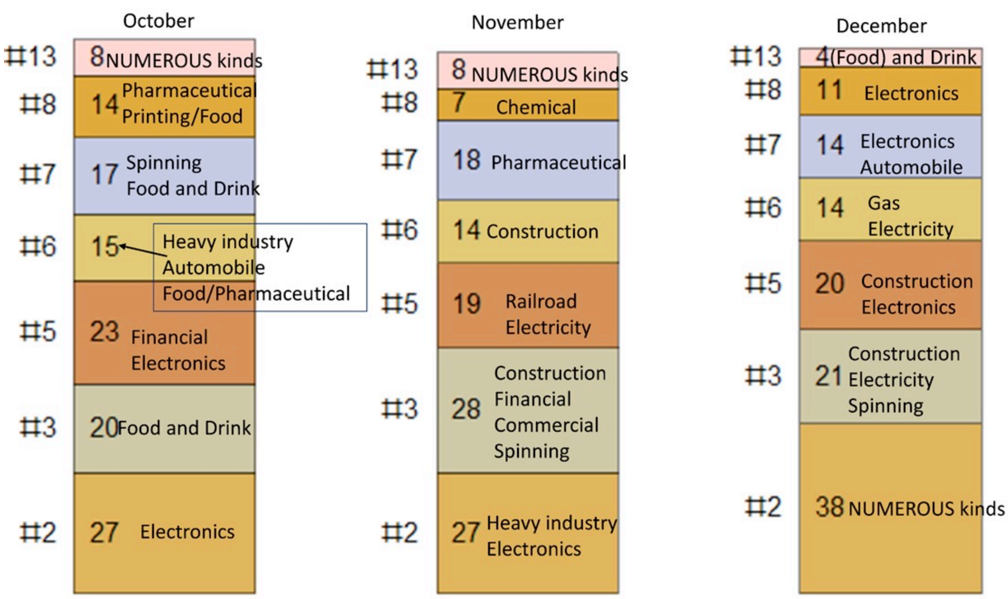

Figure 2: Monthly movements on the numbers of damaged industries involved in each damaged Brand-Eigenvector. From the left, October, November, and December.

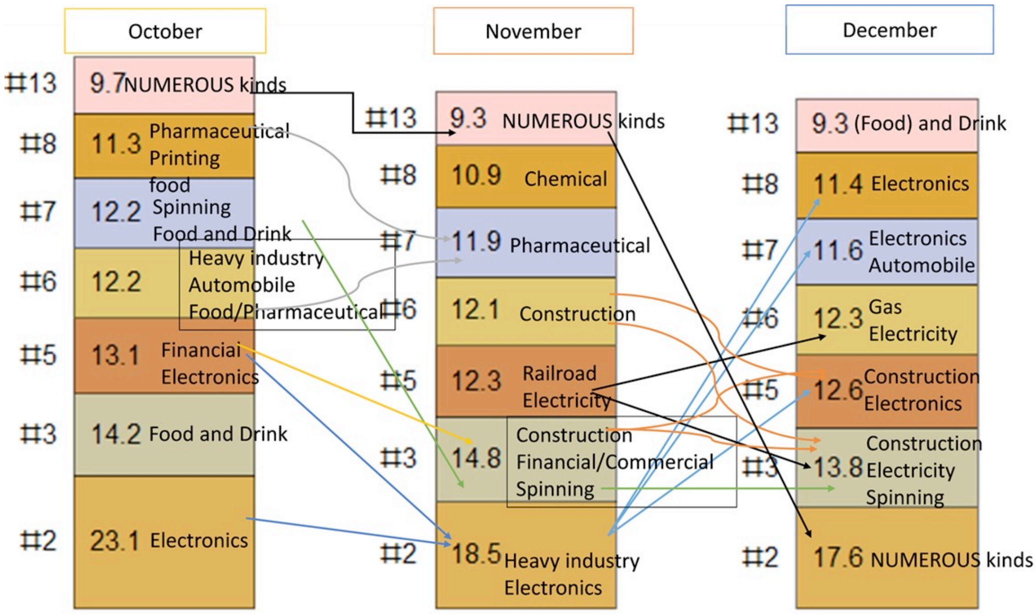

Figure 3: Monthly movements on the eigenvalues of each damaged Brand-Eigenvector. From the left, October, November, and December.

Cause and Effect Relationship between Japanese Insurance Companies and the Thai Flood

In the section, we would like to reveal the cause and effect relationship between Japanese insurance companies and the Thai flood from the result of the SVD. The data used in this research is also the Nikkei 225 during three months from October to December 2011. We conducted SVD on each month. The matrix size on each month is 225 (companies) times 20 (days). Hence, we can obtain $20 = \mathrm{Min}(225, 20)$ principal components each month.

In Japan, there are three representative general insurance companies: (1) Tokio Marine & Nichido Fire Insurance Co., Ltd., (2) MS&AD Insurance Group Holdings, Inc., and (3) SOMPO Japan Nipponkoa Insurance Inc. The earthquake happened on 11th March, and the Thai flood occurred in the beginning of October. The effect by the flood was considerably large because there were a lot of damaged Japanese companies tried to receive insurance supports from the insurance companies. In the period October to December, these companies' stock prices were declining as shown in Fig. 4 to 6. The drift coefficients (average growth rates) of the three companies were negative. According to a website, CostDown (http://www.costdown.co.jp/blog/2011/12/post_2180.html), the incurred claims by the Thai flood on the major insurance companies were enormous as shown in Table 1.

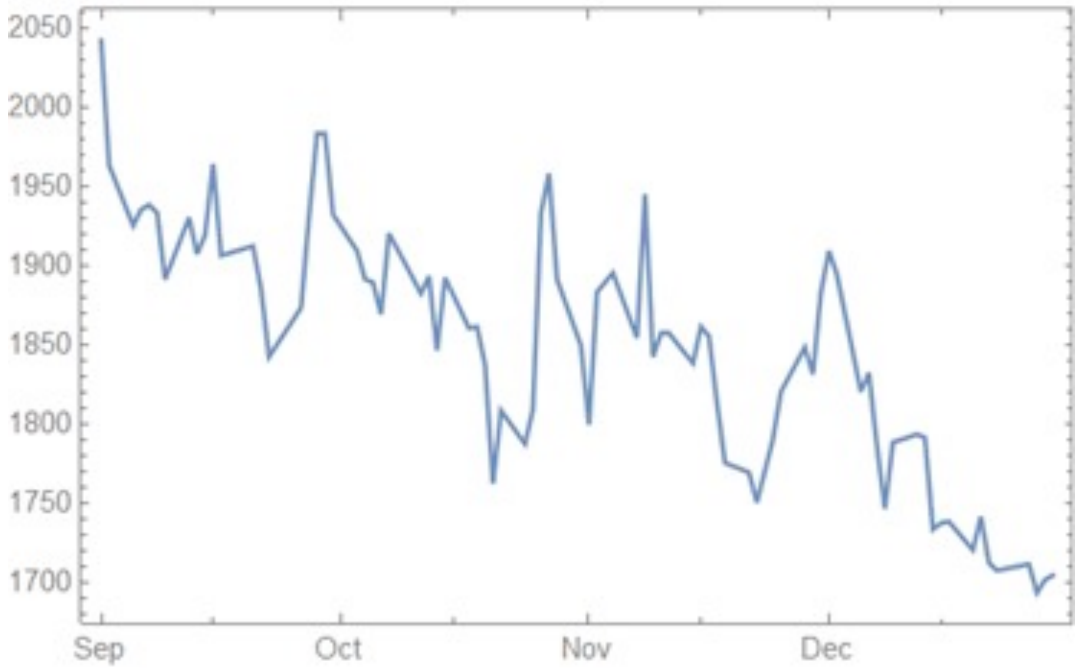

Figure 4: The Stock Price Change of Tokio Marine & Nichido Fire Insurance Co., Ltd.

Table 1: Estimated Incurred Claims by the Thai Flood on Insurance Companies

	TM&NF	MS&AD	Sompo Japan
Estimated Incuresd Claims by the Thai Flood (JPY)	110.0 billion	198.0 billion	94.1 billion
Estimated Incuresd Claims by the Thai Flood (USD)	1.409500 billion	2.483280 billion	1.205760 billion
*1JPY = 0.01281USD on 12/5/2011			

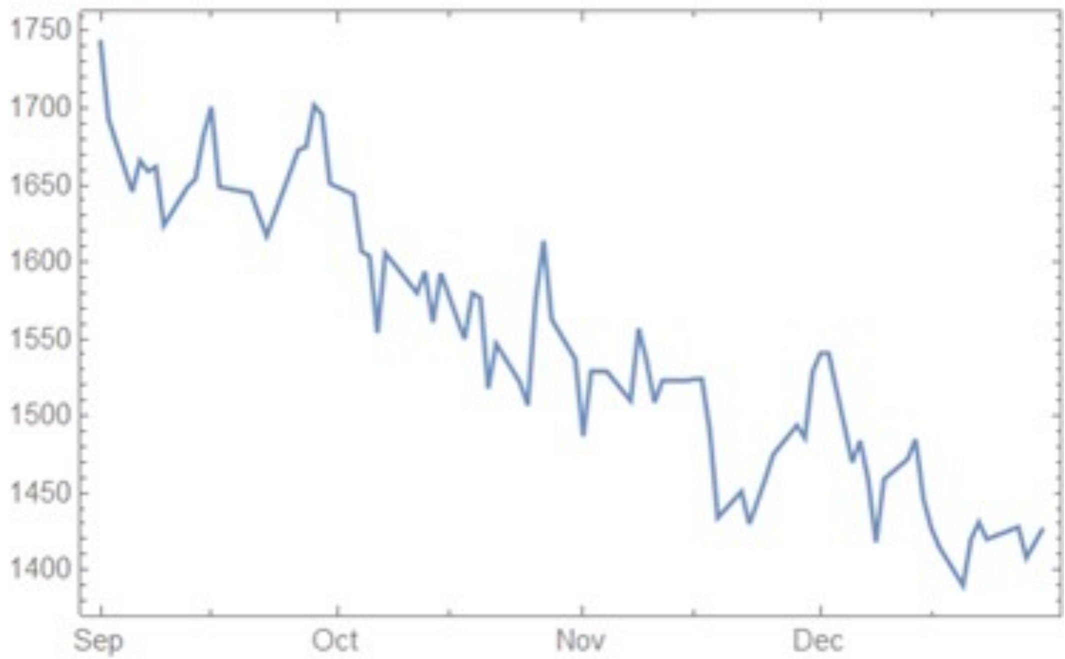

Figure 5: The Stock Price Change of MS&AD

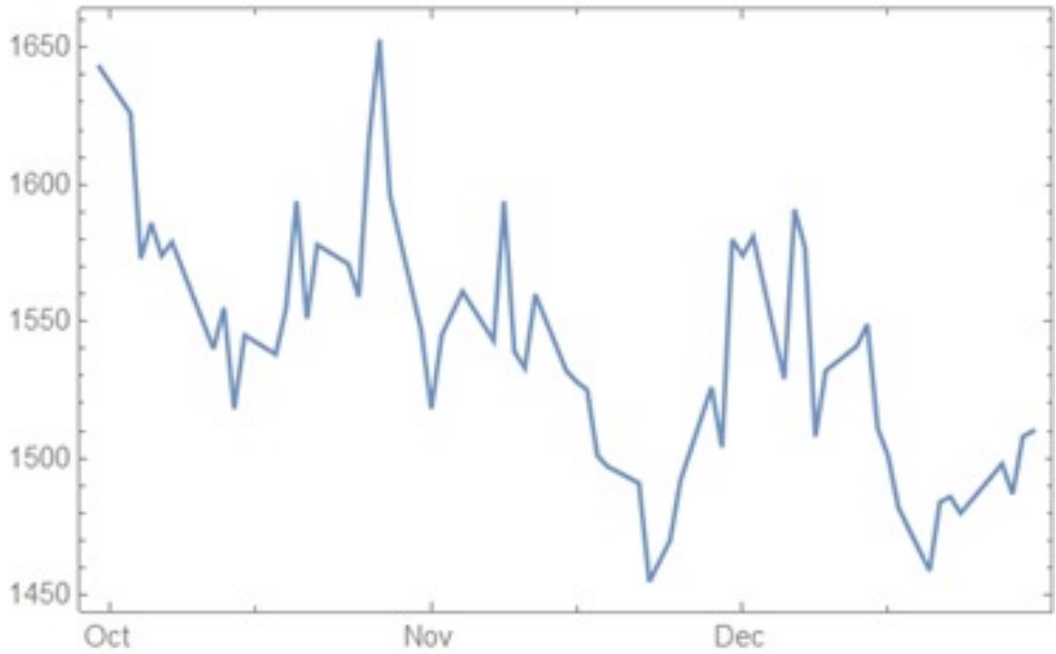

Figure 6: The Time Stock Price Change of SOMPO

First, we shall describe the analysis results on the Oct. data. From the SVD result, we found that Brand-Eigenvector #5 was the flood damaged company class. In more precise expression, that is the negative part of Eigenvector #5. As shown in Fig. 7, the Brand-Eigenvector #5 negative part includes Nikon, Pioneer and so forth. We know that these companies have been damaged. Therefore, the group is considered to be the flood damaged class. There we found that SOMPO, the insurance company, also appeared in the class with the large element value -1.32 together with Pioneer and Nikon.

We shall show you another result about SOMPO that is SOMPO's all element values on all principal components (See Fig. 8). As the total number of principal components in Oct is 19, the number of SOMPO elements is also 19 (See Fig 8).

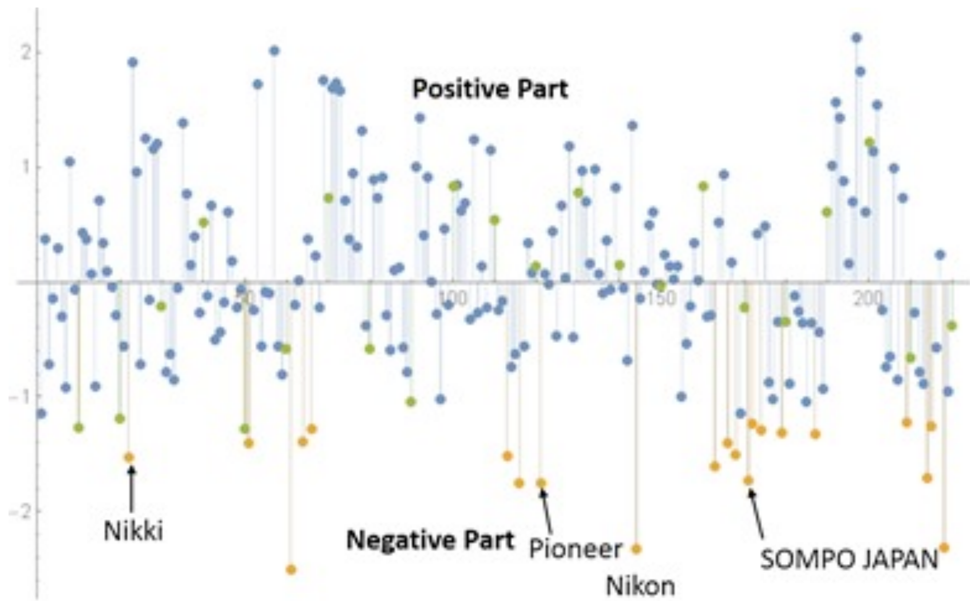

Figure 7: In October, the Brand-Eigenvector #5

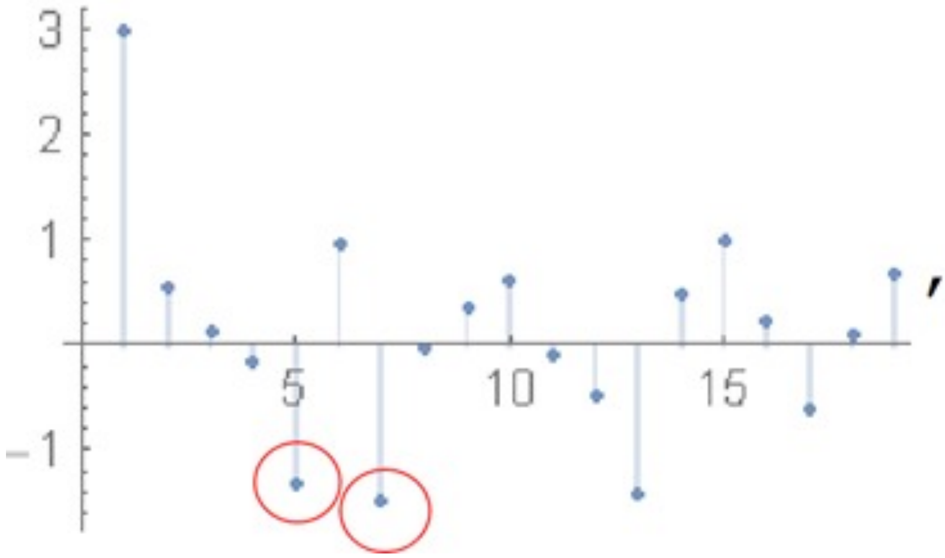

Figure 8: SOMPO element values in October on all principal components. The absolute values are larger on #5 and #7.

There, the absolute element values of SOMPO on #5 and #7 are larger than others. Because the Brand-Eigenvector #5 negative part can be interpreted as the flood damaged company group, we could say that SOMPO must have been damaged by the flood.

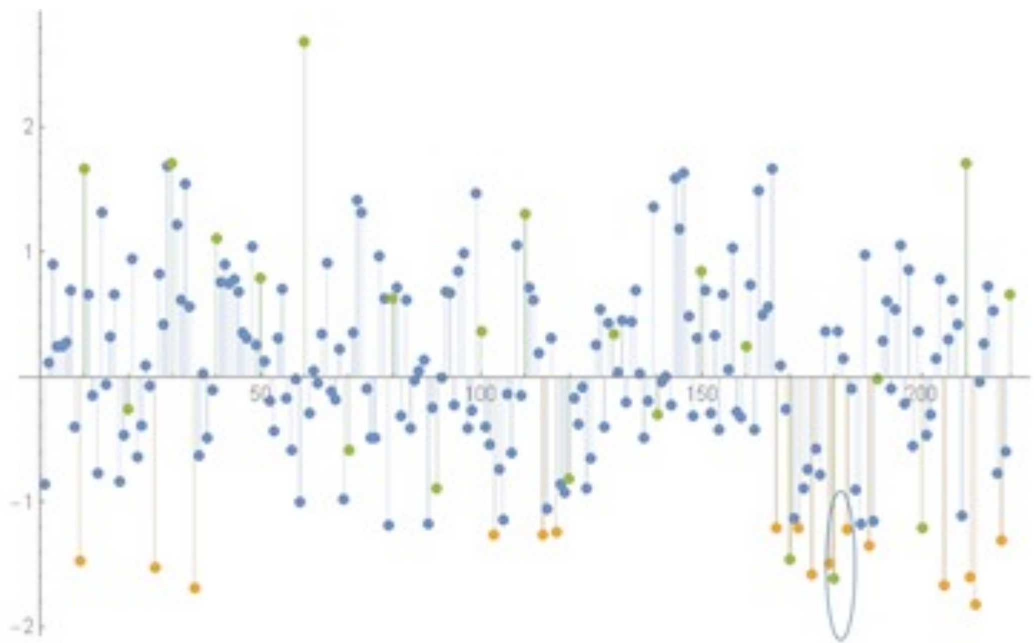

Figure 9: The Brand-Eigenvector #7 in October. The circle mark shows the three major insurance companies.

Next let us see the Brand-Eigenvector #7 (see Fig. 9). There in the positive part, we found many flood damaged companies such as Nikon, Torey, Nikki and so forth. On the other hand, when we see the negative part of the Brand-Eigenvector #7, we could see many no flood-damaged companies and there are the abovementioned three major insurance companies. In the Brand-Eigenvector #7, the positive direction shows the positive damaging level by the flood. We can, therefore, say the Brand-Eigenvector #7 negative part shows no tendency corresponding to the flood damages.

Time Series Movement of Effects

In the section, we evaluate the time series movement of damage effects. First we shall see the Nov. data results. In Fig. 10, SOMPO element values in Nov. on all principal components are shown. The absolute value on #6 is larger than others. Therefore, we think that the #6 principal component is the feature of SOMPO. Therefore, we will see the Brand-Eigenvector #6 (See Fig. 11). There in the #6 negative part we found Nikon and Pioneer. Then we can say that this group is the flood damaged group. By comparison of the representative members, we found that the #5 negative part in Oct. had similarity to the #6 negative part in Nov. The SOMPO element value was -1.32 in #5 Oct. and -1.04 in #6 Nov. So we think that this decrease from -1.32 to -1.04 may be caused by shrinking of the flood impact on SOMPO. Table 2 shows this SOMPO element values' time series movement.

Next let us see the Dec. results. In the Dec. results, we cannot find SOMPO in the flood damaged company groups. SOMPO appeared, however, in #5 Dec. as shown in Fig 12. The Brand-Eigenvector #5 negative group included other two insurance companies. It may mean that the Brand-Eigenvector #5 negative group represents the general tendency of the Japanese insurance companies at the time and there is no effect by the Thai flooding.

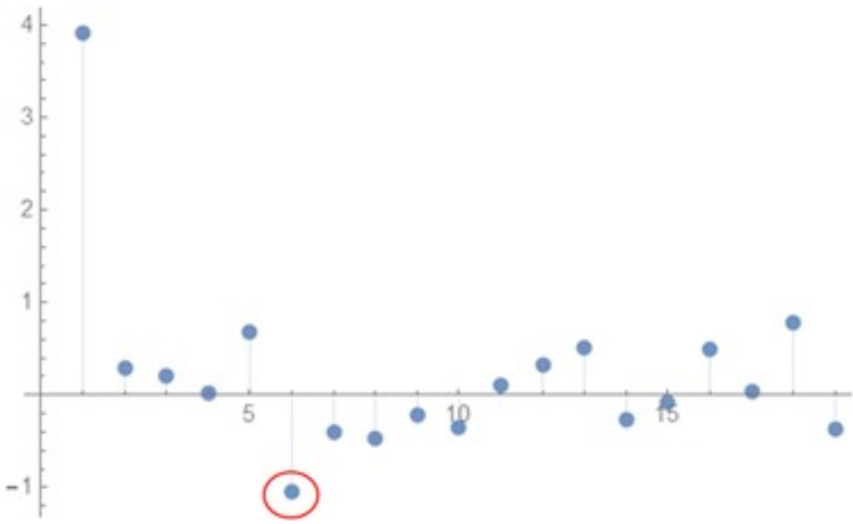

Figure 10: SOMPO element values in November on all principal components. The absolute values on #6 is larger.

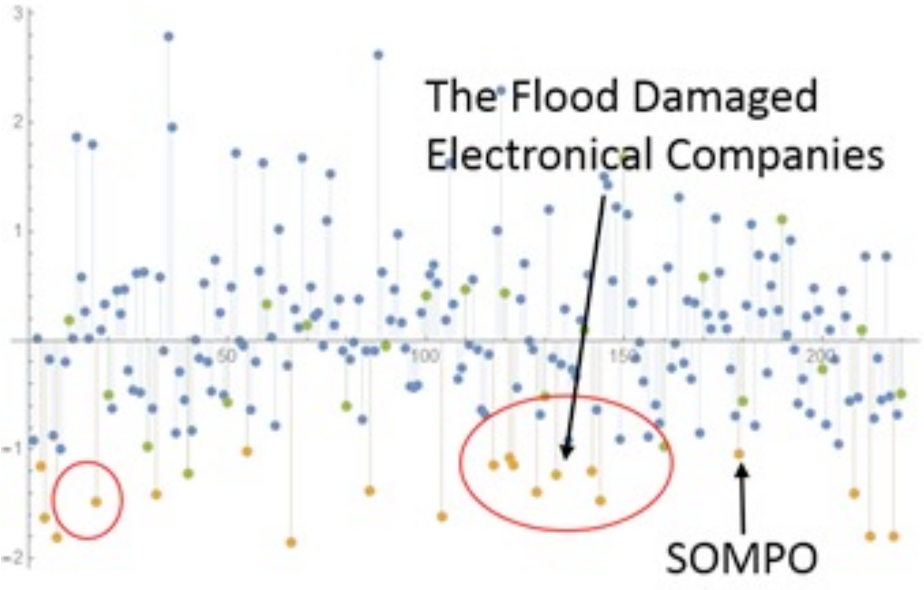

Figure 11: The element data of the Brand-Eigenvector #6 in November.

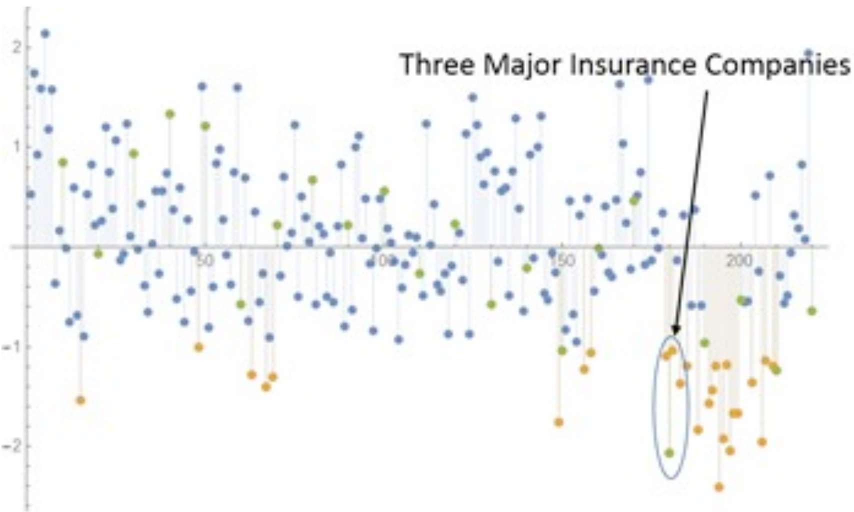

Figure 12: The element data of the Brand-Eigenvector #5 in December

Table 2: SOMPO Element Values

MONTH	Thai Flood	Non Thai Flood
OCT	1.32 (#5 negative)	1.49 (#7 negative)
NOV	1.04 (#6 negative)	None (<1.2)
DEC	None (<1.2)	1.09 (#5 negative)

Conclusion

In the paper, we propose, as a new time series economics data analysis method, an integrated approach of Singular Value Decomposition on stock data. Concerning the Thai flooding effects on the Japan's economy, as unexpected moves, we have found the serious harms on the Japanese insurance companies. From the SVD result, we found that Brand-Eigenvector #5 was the flood damaged company class because there are the Thai flood damaged companies such as Nikon and Pioneer. With these companies, SOMPO Japan exists in Brand-Eigenvector #5 in Oct; hence, we could say that SOMPO was damaged by the Thai flood. To support this result, we searched web news about incurred claims by the Thai flood, we found out one website, CostDown, and this website reported the amounts of estimated incurred claims by the Thai flood on Japanese insurance companies. The total payment of each insurance company is a tremendous loss; therefore, we proved that there is a causal and effect relationship between the Thai flood and Japanese insurance companies. The most possible reason is that there are lots of flooded Japanese factories and brunches in Thai, and as a result, Japanese insurance companies had to pay a huge amount of money. The paper showed the correspondence between the eigenvectors and the web news data. This approach is really helpful and eye-opening to contribute to people, not only professionals but also people who do not have a detailed knowledge of a specific topic. The reason is that a normal stock price change graph cannot tell us what kind of factor, a natural disaster, a policy, and so on, affects to its stock price. In addition, it is really difficult to find out a convincing factor for even professionals especially when there are more than two factors. This approach does not require people to know a lot of detailed knowledge about a topic in the field. So people can analyze a cause and effect on its topic. Therefore, this approach can let more people analyze topics much more easily than now. We will continue to study the natural disaster damages on Japanese stock market.

Acknowledgement

We thank Prof Takako Hashimoto for her wide range of knowledge about Thai economy that helps our research. This research was partly supported by funds from the Telecommunications Advancement Foundation research project in 2015 to 2016. In addition, this study was partly supported by a grant from the Gakushuin University Computer Centre special project 2016.

References

B. Efron. (2010). *Large-Scale Inference*. Cambridge University Press.

C. M. Bishop. (2006). *Pattern Recognition and Machine Learning*. Springer.

Y. Shirota, and B. Chakraborty. (2015). *Visual Explanation of Mathematics in Latent Semantic Analysis*. Proc. of IIAI International Congress on Advanced Applied Informatics 2015. 12-16 July, 2015, Okayama, Japan, pp. 423-428.

Y. Shirota, and B. Chakraborty. (2016). *Visual Explanation of Eigenvalues and Math Process in Latent Semantic Analysis.* Information Engineering Express. Information Engineering Express, vol. 2, no. 1, pp. 87-96.

M. F. Lubis, Y. Shirota, and R. F. Sari. (2015). *Thailand's 2011 Flooding: its Impacts on Japan Companies in Stock Price Data.* Gakushuin Economics Papers. vol. 52, no. 3, pp. 101-121.

M. F. Lubis, Y. Shirota, and R. F. Sari. (2015). *Analysis on Stock Price Fluctuation due to Flood Disaster using Singular Value Decomposition Method.* Proc. of JSAI International Symposium on AI. TADDA (Workshop on Time Series Data Analysis and its Applications), 16-18 Nov. 2015, Hiyoshi, Japan.

S. Sukegawa. (2013). Chapter 3: *Effects of the 2011 Thai Flooding on Industries and Companies*. p.^pp. 73-96 (written in Japanese): IDE-JETRO.

P. Cooke. (2013). European Planning Studies, Special Issue: Local and Regional Development (LoRD) across Global Value Chains, Production Systems and Innovation Networks, vol. 21, no. 7, pp. 1081--1094, 2013

M. Potters, J.-P. Bouchaud, and L. Laloux. (2005). *Financial Applications of Random Matrix Theory.* Old Laces and New Pieces. arXiv preprint physics/0507111, 2005.

G. W. Anderson, A. Guionnet, and O. Zeitouni. (2009). *An Introduction to Random Matrices (Cambridge Studies in Advanced Mathematics)*. Cambridge University Press.

J.-P. Bouchaud, and M. Potters. (2011). *Financial Applications of Random Matrix Theory*. Oxford University Press, 2011.

V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, and H. E. Stanley. (2000). *A random matrix theory approach to financial cross-correlations.* Physica A: Statistical Mechanics and its Applications. vol. 287, no. 3–4, pp. 374-382, 12/1/, 2000.

V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, T. Guhr, and H. E. Stanley, (n.d.). *Random matrix approach to cross correlations in financial data.* Physical Review E, vol. 65, no. 6, pp. 066126.

Contact email: 16122006@gakushuin.ac.jp, yukari.shirota@gakushuin.ac.jp