

Decline Patterns of Stock Prices by Disasters — Case Study of May 2019

Kenji Yamaguchi and Yukari Shirota

Abstract—We shall measure the US-China trade friction impact in May 2019 on Japanese and US companies' stock prices. When the President' remark issued, the stock prices decreased. The decline patterns are in general dependent on the industry fields. We shall find a difference of decline patterns of the stock price movement. The data used are one of Japanese companies that have a lot of transactions with Chinese companies. They are machinery manufacturing companies (B2B transaction ones) and necessities selling companies (B2C ones) such as baby items, cosmetics, and clothing. We traced the time series data changes visually by our developed disaster impact graphs and finally found the pattern difference between the two fields. The machinery manufacturers' stock prices clearly fall and keep low. The necessities makers' pattern shows fluctuating declines.

Index Terms—Disaster impact on stock prices, Us-China trade friction, random matrix theory, singular value decomposition, disaster impact network.

I. INTRODUCTION

We have been investigated the time stock price changes. In the Tokyo stock market on the 7th May, 2019, the decline in economic sensitive stocks such as electrical equipment and machinery was noticeable (from Newspaper Nikkei 2019/05/08). The reason of the decline is that on May 5, 2019 President Trump stated that the previous tariffs of 10% levied in \$200 billion worth of Chinese goods would be raised to 25% on May 10 [1]. If there exists a **trading friction between the USA and China**, almost all Japanese companies would have large effects. In the paper, we would like to find the stock price movement patterns among Japanese companies at the trading conflict. Especially, China-related companies in Japan decreased the stock prices. The decline reason is the concern that the global economy will slow down due to the tariff increases. It is remarkable that Chinese orders for control machines and electronic parts decreased then owing to the influence of the trade friction. This is derived from a decrease of a business-to-business (B2B) transaction. Another mode is a business-to-consumer (B2C) transaction. Japanese suppliers offer Chinese customers large amounts of cosmetics and baby products, and so forth. We analyzed the one month stock price movement in the May and then we found that the B2B based company stock price pattern is quite different to one of the B2C based companies. The B2B

based companies stock prices could not get recovered quickly, compared to the B2C based companies.

In the next section, we shall explain the data we used and the method. Then In Section III the results of the analysis will be shown and our evaluation on this will be described. Finally, we shall conclude the paper.

II. DATA AND METHOD

In the section, we shall explain the data and method we used. The data is **50 companies titled “Nikkei China-related stocks”** in the first section of the Tokyo Stock Exchange. They are the companies selected by Nikkei from major Japanese companies that are actively developing business in China. The data period is from **2019/04/24 to 2019/06/06** of which sales days are 26 days. The method is **Random Matrix Theory** (abbreviated by RMT). Historically, many physical phenomena have been successfully solved using RMT, and remarkably a great number of applications to finance have arisen during the last years. In 2000, Plerou used RMT to find cross correlations in financial data [2], [3]. Since then in the field of econophysics, RMT has been widely used to make portfolios and to monitor company network [4], [4]-[12].

The RMT math process is SVD (Singular Value Decomposition) [13], [14]. The SVD is used in various kinds of applications; For example, the text mining LSA (Latent Semantic Analysis) uses the SVD. Concerning the SVD math process, Shirota et al. visually explain the intrinsic meanings and interpretation of the eigenvectors/principal components, so that readers can easily and deeply understand SVD [15]. In RMT, we conduct the SVD on the standardized return values of stock price data [2], [16], [17].

The return value is 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. As that is a natural logarithm of the ratio, if the today's price is greater than the precious one, then the ratio will be greater than one and the logarithm value will be positive. And if the today's price is less than the precious one, then the ratio will be less than one and the logarithm value will be negative.

Because different stock values have varying ranges of means and volatilities, the return values should in advance be standardized, so the mean value becomes 0 and the standard deviation becomes 1.

The proposed method is conducted as follows: First, we conduct SVD on the time series data matrix X of stock price return values, so that we can obtain, as the output, the matrices U , W , and V^T . Then, we have gotten two kinds of

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K. Yamaguchi is with Science & Education Center (SEC), Ochanomizu University, Japan (e-mail: yamaguchi.kenji@ocha.ac.jp).

Y. Shirota is with the Faculty of Economics, Gakushuin University, Japan (e-mail: yukari.shirota@gakushuin.ac.jp).

eigenvectors obtained by (U W) and by (S V^T). We call the eigenvectors (1) **Brand-Eigenvector, obtained by (U W)**, and (2) **Dailymotion-Eigenvector, obtained by (S V^T)**. The principal component means a company group with a similar movement. For example, we can get a bank group, a telephone group, an automaker group, and so forth. A principal component can show a damage pattern when the target is damaged companies.

Let us explain the RMT. We represent eigenvalues of the Brand-Eigenvectors and Dailymotion-Eigenvectors as $\{\sqrt{\lambda_i}\}$. On the other hand, we make the matrix $C = \frac{1}{T}XX^T$ which is called the **correlation matrix**. The eigenvectors of the correlation matrix C are $\{\lambda_i\}$. The proof for the calculation is shown in [15]. RMT offers the eigenvalue distribution of the correlation matrix of which data is **random** one follows

$$\rho(\lambda) = \frac{1}{2\pi\lambda} \sqrt{(\lambda_+ - \lambda)(\lambda - \lambda_-)}$$

$$\lambda_{\pm} = 1 + \frac{1}{Q} \pm 2\sqrt{\frac{1}{Q}}$$

$$Q = \frac{T}{N}$$

$\rho(\lambda)$ shows the random range. The constraint to use the expressions $\rho(\lambda)$ exists and that is **Q > 1 and N > 300** where **the matrix X size is N (companies) times T (days)** [4]. Then, we would like to extract the principal components' eigenvalues λ which exists **outside the random range which satisfy $\lambda > \lambda_+$** .

However, it is difficult for us to meet the constraint **Q > 1 and N > 300** and to obtain such a large data set. If we can use the hourly or every minute data, we can meet the constraint **N > 300**. However we use the database Nikkei financial quest by Nikkei (<http://finquest.nikkeidb.or.jp/ver2/online/>) which offers only daily data. We cannot obtain the hourly data from the database. In general, it is impossible for us university researchers to use the hourly data. Plerou also used the **daily data for over several years**, so that they can meet the constraint **Q > 1 and N > 300** [2].

Let me explain our approach. The existing RMT approach set the null hypothesis that the data move at random. Then, they confirm that they can reject the null hypothesis and then extract the skewed/featured eigenvalues. On the other hand, we set the target is the status just after the disaster which is not the peaceful/stable status. Our objective is **to find a similar movement company group**. We use first the damaged company which we know well that the company was severely damaged.

To extract the skewed/featured parts, we shall take their approach using $\lambda > \lambda_+$. However, we cannot meet the **Q > 1 and N > 300** condition. As we concentrate on the cause and effect relationship of the disaster and the stock decline for a short period, the period is just a week through a month or so.

Just after the disaster, the impact of the disaster is gigantic just like the membrane musical instrument is hit. Then gradually the disaster effect decreases and the eigenvalue of the featured principal component also decreases and finally disappears. How should we measure the boundary of those? In other words, that is the **normality test**. To conduct the **normality tests for the correlation matrix C**, we observe the **probability distribution of the matrix C elements** (See

Fig. 1). Since a perfect normal distribution would have **skewness zero and kurtosis 3**, we may see whether the distribution of the elements of C in the periods of crisis are not normal [10].

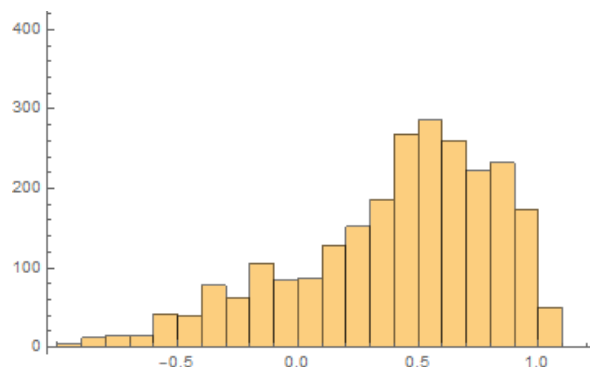


Fig. 1. Distribution of the correlation matrix C elements of the 6th period which is skewed from a normal distribution.

Another measurement is **the distribution of eigenvalues of the matrix C**. First we plot the eigenvalues in order of magnitude (See Figure 2). Then we observe a frequency distribution (histogram) of the eigenvalues of the C with the above-mentioned $\rho(\lambda) = \frac{1}{2\pi\lambda} \sqrt{(\lambda_+ - \lambda)(\lambda - \lambda_-)}$ (See Fig. 3).

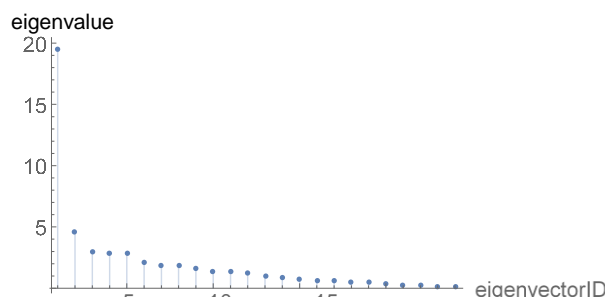


Fig. 2. The original 24 eigenvalues of ones in Fig. 1.

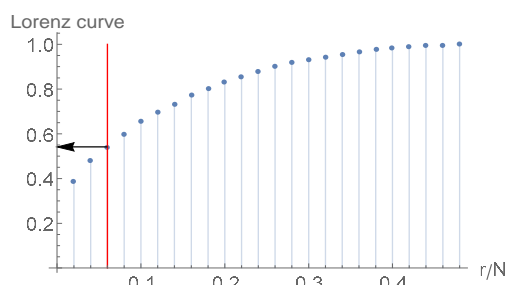


Fig. 3. Frequency distribution of the eigenvalues of the correlation matrix C and the theoretical distribution $\rho(\lambda)$ is superimposed on it.

Although the matrix C we use cannot meet the normality constraint **Q > 1 and N > 300**, that distribution $\rho(\lambda)$ is helpful when we extract the skewed/featured eigenvalues. Suppose that we obtained 24 principal components from the SVD and the eigenvalues are supposed to be as shown in Fig. 2. An eigenvalue is an impact factor of the corresponding principal component. From Fig. 2, we can see that the first principal component is the dominant one, compared to others. To measure the amplitudes, we use the **Lorenz curve** [4]. Fig. 4 shows an example Lorenz curve. The raw eigenvalues are shown in Fig. 2. The impact of λ_r is defined as $P_{<}(\lambda_r) = \frac{1}{N} \sum_{i=1}^r \lambda_i$. In Fig. 4 Lorenz curve, the first, second, and third

eigenvalues dominate 54% of the whole eigenvalues' strength in which the theory says that $\sum_{i=1}^N \lambda_i = N$.

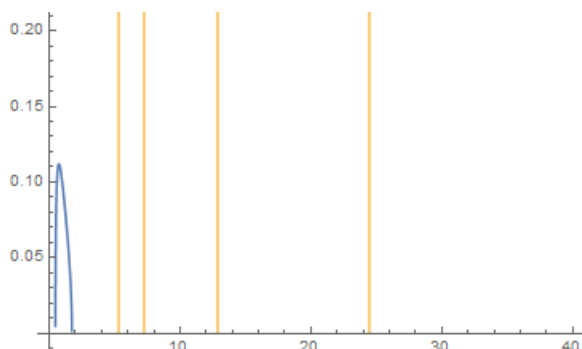


Fig. 4. Lorentz curve of the eigenvalue amplitudes.

The interpretation of the principal component direction with positive/negative must be done by our decision. The positive side and negative side in the same principal component show the opposite meaning. For example, the positive numbers show the damage level and then the negative numbers show the non-damage level. The direction itself has no meaning. To explain that, let's consider the **Principal Component Analysis (PCA)** [13]. In PCA, the direction of the principal component has no meaning (See Fig. 5). It does not matter which direction is positive. The important thing is the interpretation of the positive/negative meanings.

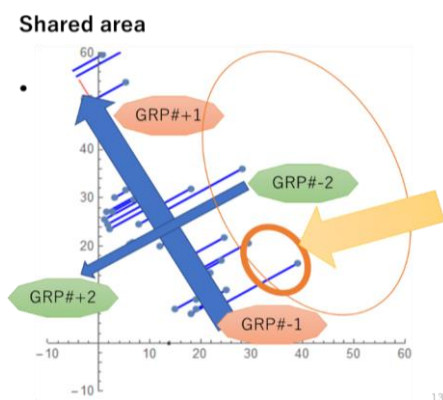


Fig. 5. Direction of a principal component in PCA. It doesn't matter which way you take the positive orientation. The data {x, y} here are a sample data.

In the paper, we represent a principal component (Brand-Eigenvector) by “[#number]” such as #7 and the company group of the positive side by “GROUP# [+/-] [number]” such as **GROUP#+7** and **GROUP#-7**. We set the **threshold level such as 1.2**. In one Brand-Eigenvector, there are 50 company factors. The company with the factor greater than the **threshold level** is selected as the positive GROUP representative company. On the other hand, the company with the factor smaller than the minus threshold level is selected as the negative GROUP representative company.

In general, in a financial analysis, RMT is utilized to find the stable company classes. Using the extracted stable classes, they make an excellent performance portfolio. Our research goal is, however, different from their approaches, and we would like to find and investigate the time series effects of the disaster on stock prices. The damaged company network would change day by day. Therefore, we extend the period of the input stock price data by one day.

The days of our input data are 2019/4/24, 2019/4/25, 2019/4/26, 2019/5/7, 2019/5/8, 2019/5/9, and so forth. Then the starting day is fixed to be 2019/04/24. The **period 4** means the period from 2019/04/24 to 2019/5/7 of which input matrix size becomes **50 (companies) times 3 (return values)**, because the return value is a ratio. The **period 5** means the period from 2019/04/24 to 2019/5/8 of which input matrix size becomes 50 times 4. We would like to investigate the time series change of principal components of these **period 4 to period 26**.

To investigate the time series change visually, we have developed the graph drawing system named “**Disaster Impact Network**” drawing system. The resultant sample network is showed in Fig. 6 which consists of **GROUP#-1** and **GROUP#-2**. We can see that there are three companies have both features of **GROUP#-1** and **GROUP#-2**. The figure shows the company's element value in the GROUP.

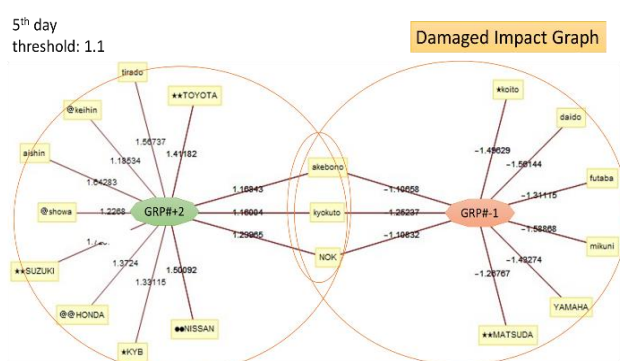


Fig. 6. The damaged impact graph to show the shared area with three companies on Fig. 5.

The network drawing algorithm of the **Disaster Impact Graph** will be explained. First, we give the system the data of the **diffusion origin company** which means an epicenter such as Nikon. The user selects the origin company as one on which he/she is interested. The drawing system traces the correlations of the origin company.

Another important parameter is the **threshold value** to select representative companies among each Brand-Eigenvector. Suppose that we take the period 25. Then the input matrix size is 50 times 24. The number of eigenvectors becomes 24 which is $\min(50, 24)$. Each eigenvector has 50 company elements. If the threshold is given 2.0, then companies with its element value **> 2.0 or < -2.0** are selected as representatives. Then from one GROUP, the positive side group and the negative side group are made such as **GROUP#+2** and **GROUP#-2**.

The drawing algorithm of the disaster impact network is as follows:

1. Set the matrix and execute the SVD
2. Find GROUPs of the origin company and draw the network around the origin company; the company may belong to several GROUPs.
3. For each GROUP among the above GROUPs, find the representative companies and draw the graph of the GROUP

The **depth of the network tree** is another parameter which defines the depth of the tree from the origin company. If the depth is two, then the tree of depth two from the origin will be drawn.

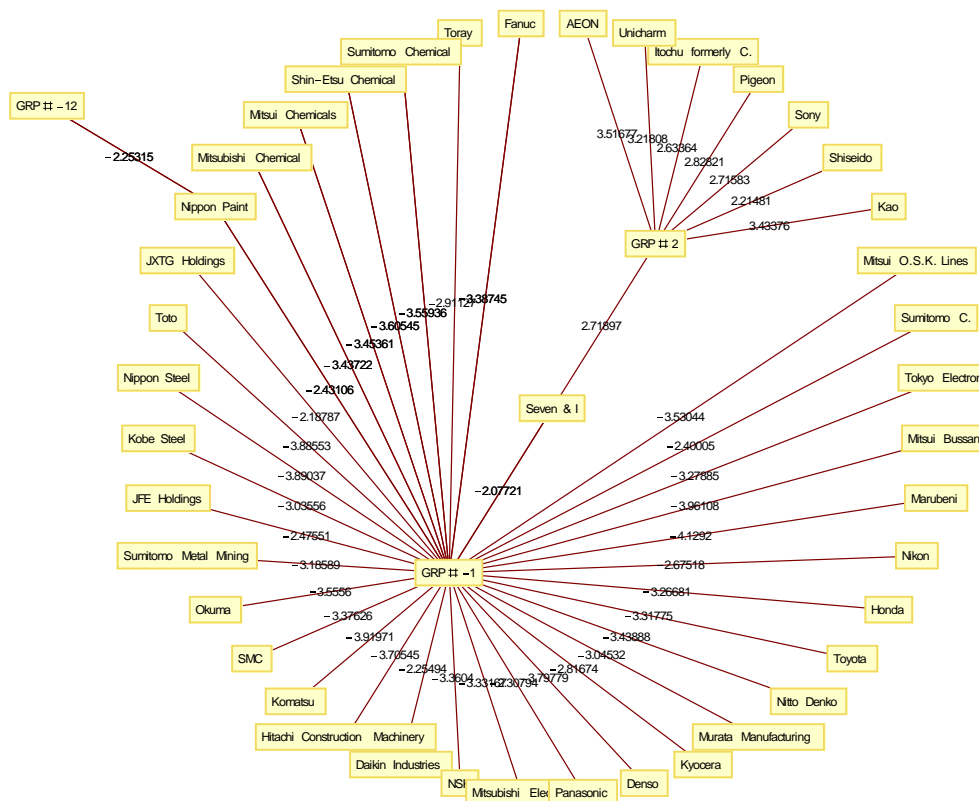


Fig. 7. Disaster impact network of the period 24 (2019/04/24 to 2019/06/04).

III. EVALUATION

In the section, we shall explain the features from the time series change set of the principal components depending on the periods from 4 to 26. First let's see the period 24 in Fig. 7. We found that the **machinery companies (GROUP#-1)** and the **daily necessities companies (GROUP#+2)** were clearly separated on the period 24. The origin company there was "FANUC", and other parameters were the depth 2, and the threshold 2.0. Let's see the inside of the GROUPS. The GROUP#-1 includes many manufacturing companies with a lot of demands in China. In addition, GROUP#-1 also includes the general trading companies that trade with China. The manufacturing companies include machinery, electronics, and automobiles. On the other hand, GROUP#+2 consists of daily necessities companies; they are the two large shopping mall companies, the two baby diaper makers, the company of baby bottle disinfectant and pacifier, and the cosmetics maker. One general trading company and one electronics company are also included in GROUP#+2. Because the first eigenvalue is greater than the second eigenvalue, the impact of GROUP#-1 is greater than one of GROUP#+2 (See Fig. 2).

Then we can say that the damages of manufacturing companies were greater than ones of the daily necessities companies. There exists one company "SEVEN&I holdings" in the shared area of both GROUP#-1 and #+2. Later we will describe the company again.

In Fig. 8, two graphs of stock prices comparison (not return values) are shown. KOMATSU and Hitachi Construction Machinery are representatives of GROUP#-1 with element values -3.9 and -3.7. On the other hand, AEON and KAO are representatives of GROUP#+2 with element values 3.5 and 3.4. KOMATSU and Hitachi CM had a large decline from third

to 6th day and then continued to keep low. On the other hand, AEON and KAO had a decline on 6th or 7th day but they showed quick recovery at least on 13th day but again they decreased from 19th to 24th approximately.

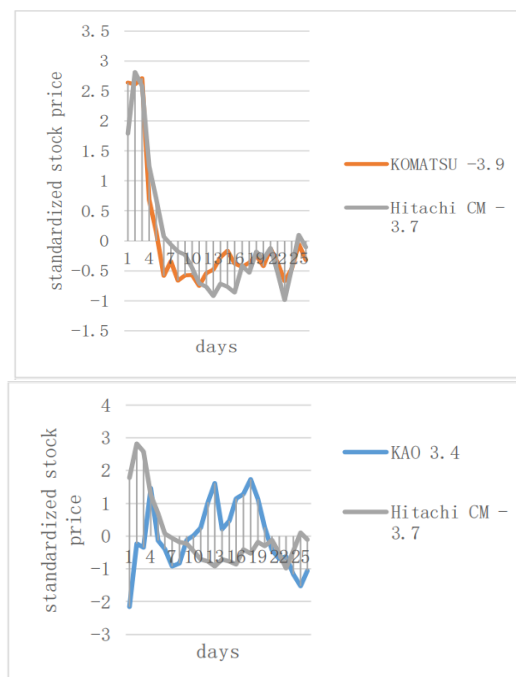


Fig. 8. Stock price comparisons of different company groups' representatives.

The AEON and KAO which are representative of daily commodities selling companies showed a quite different pattern, compared to the pattern of the two machinery companies. The B2B transactions to sell machinery is in general not agile. On the other hand, selling necessities to consumers is a light transaction and the stock prices are likely

to change easily due to some effects. We think that the latter consumption can be easily changed upward or downward. Then the stock price in general tends to fluctuate.

Then let us trace the two groups movement. In Fig. 4, the period 25 disaster impact network is shown. Compared to the 24 period (Fig. 5), GROUP#-1 then has no large change, keeping to be the most damaged group. GROUP#+2 has no large change, either. However, AEON (the shopping mall company) and Pigeon (the baby bottle disinfectant company) are added as the representatives with GROUP#-1. Then, the two greatest shopping mall companies Seven & i and AEON have had the both GROUP features in Fig. 4. We think that that may be a symptom of a fusion of the two GROUPS.

Anyway, we can say that the stock prices of companies selling necessities are susceptible to external influences and tend to change.

IV. NORMALITY TESTS FOR THE CORRELATION MATRIX

In the section, we shall investigate whether the correlation matrix is at random status or not. What we are interested in is only the status not at random. In addition, we would like to extract the eigenvalues out of the range of random ones. In Fig. 9, the skewness of the distribution of the Matrix C elements. First on the period 4 and 5 a large negative skewness is shown.

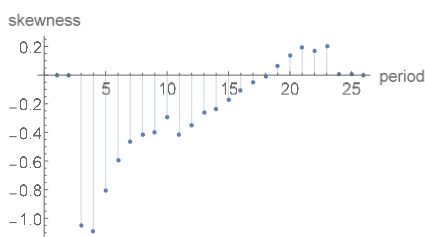


Fig. 9. Skewness of the distribution of the correlation matrix C elements from the fourth period to the 26th period.

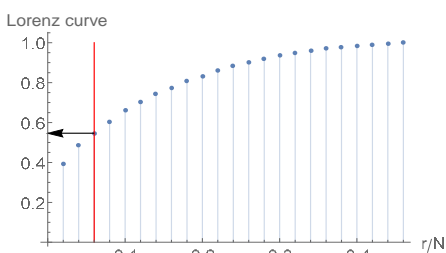


Fig. 10. Lorenz curve of the 24th period.

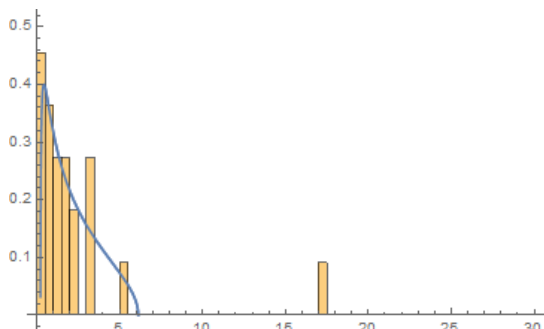


Fig. 11. Frequency distribution of the eigenvalues of the correlation matrix C of the 24th period and the theoretical distribution $\rho(\lambda)$ superimposed on it.

Then the skewness decreases gradually and finally changes the skewness from negative to positive. Just skewness

movement, we cannot identify whether the period 24th has enough skewed or not. Then, we see the Lorenz curve of the eigenvalue amplitudes (See Fig. 10).

The first and second ones dominate about 50% of the whole amplitudes. Seeing Fig. 11 which shows the frequency distribution of the period 24th eigenvalues, we can see that at least one eigenvalue is greater than the $\rho(\lambda)$ range. From the Lorenz curve and the frequency distribution of the eigenvalues, we can say that on the 24th period the first and second principal components are not random ones. Then we can convince the two GROUPS are effects by the disaster.

V. EVALUATION

In the section, we survey the US companies to know whether we can spot the difference between machinery manufacturing companies and necessities production companies as well as the Japanese companies.

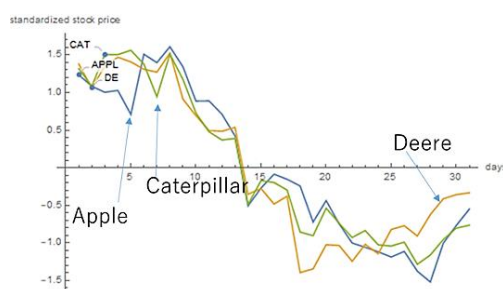


Fig. 12. Stock prices of Apple, Deere, and Caterpillar.

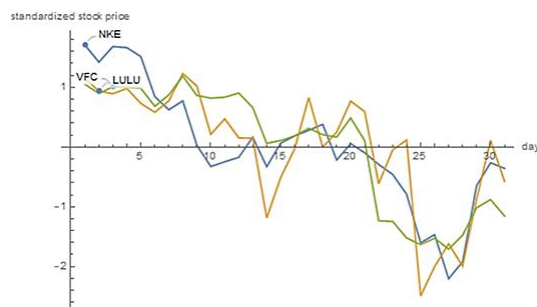


Fig. 13. Stock prices of NIKE, Lululemon, and V.F.

The data we used is stock prices of New York Stock Exchange (NYSE). The data period is the same as the Japanese stock data; they are from 2019/04/24 to 2019/06/06. The selected companies from NYSE are as follows:

- (1) machinery: Caterpillar, Deere, and Apple and
- (2) necessities: NIKE, Lululemon, V.F.

When we select the companies, we referred the U.S. Company Handbook 2019 Spring/Summer by Toyokeizai-shinpousha (<https://toyokeizai.net>). Caterpillar is a construction equipment maker and a similar company to KOMATSU and Hitachi Construction Machinery. Deere is listed as the rival company of Caterpillar in the U.S. Company Handbook 2019. In addition, as the representative US manufacturing company, we added Apple. In advance, we standardize the company's data. As a result, we can see those stock prices decreased clearly as shown in Fig. 12.

As the necessities manufacturers, we selected three apparel manufacturers that the handbook featured. They are NIKE, Lululemon, and V.F. Corp. We could not find the counterpart companies in US of the above-mentioned Japanese companies; they are cosmetics, disposal diapers, shopping

malls and so forth.

NIKE is one of the biggest worldwide apparel makers and offers “The North Face”, “Vans”, “Timberland”, “Wrangler” and “Lee.” Nike is famous for the basket shoes. Lululemon is a sports fashion brand. Although we are not sure how the companies’ sales depend on China purchasing power, after the President remark in May 2019 the stock prices of them decreased. Probably the President remark affected the three companies. The decline was fluctuating as shown in Fig. 13. Seeing the decrease patterns, we saw the difference between the machinery manufacturing companies and apparel makers in US companies as well as Japanese companies.

VI. CONCLUSIONS

We surveyed the US-China Trade conflict effect in May 2019 on Japanese companies. We conducted RMT on the stock price data of 50 companies that are actively developing business in China, so that we could investigate the effects of the trading conflict between USA and China. The data period is from 2019/04/24 to 2019/06/06 of which sales days are 26 days. From the result, we found that machinery companies drastically decreased stock prices from 2019/05/07 to 2019/05/10 and then continued to keep low. Large difficulties are found when the companies got recovered from the decline; another pattern was shown in the daily commodities companies. They are two shopping mall companies, the two baby diaper makers, the company of baby bottle disinfectant and pacifier, and the cosmetics maker. Owing to Chinese large demand power, they sell a lot of daily commodities in China. Their stock movement pattern was a decline on 2019/05/09 or 2019/05/10 and showed a fluctuation and flexible recover after that. The similar patterns can be found in the same period and in the US machinery manufacturing companies and clothing companies. We would like to analyze continuously the effect of the trading war.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Yamaguchi and Shirota conducted the research. Yamaguchi analyzed the data. Shirota mainly evaluated the data. Yamaguchi and Shirota wrote the paper. All authors had approved the final version.

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REFERENCES

- [1] Trade Representative (Office of United States), “Notice of modification of section 301 action: China’s acts, policies, and practices related to technology transfer, intellectual property, and innovation,” *Federal Register - The Daily Journal of the United States Government*, 2019.
- [2] V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, and H. E. Stanley, “A random matrix theory approach to financial cross-correlations,” *Physica A: Statistical Mechanics and its Applications*, vol. 287, no. 3–4, pp. 374–382, 2000.

- [3] V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, T. Guhr, and H. E. Stanley, “Random matrix approach to cross correlations in financial data,” *Physical Review E*, vol. 65, no. 6, p. 066126, 2002.
- [4] T. Kido, X. Yang, M. Tanaka-Yamawaki, and T. Takaishi, “Historical study of major sectors in Japanese and American stock markets by means of RMT-based principal component analysis,” *TOM*, vol. 4, no. 4, pp. 104–110, 2011.
- [5] R. N. Mantegna and H. E. Stanley, *Introduction to Econophysics: Correlations and Complexity in Finance*, Cambridge University Press, 1999.
- [6] M. Potters, J.-P. Bouchaud, and L. Laloux, “Financial applications of random matrix theory: Old laces and new pieces,” arXiv preprint physics/0507111, 2005.
- [7] M. C. Münnix, T. Shimada, R. Schäfer, F. Leyvraz, T. H. Seligman, T. Guhr, and H. E. Stanley, “Identifying states of a financial market,” *Scientific Reports*, vol. 2, p. 644, 2012.
- [8] S. Maslov, “Measures of globalization based on cross-correlations of world financial indices,” *Physica A: Statistical Mechanics and its Applications*, vol. 301, no. 1–4, pp. 397–406, 2001.
- [9] D. Wang, B. Podobnik, D. Horvatić, and H. E. Stanley, “Quantifying and modeling long-range cross correlations in multiple time series with applications to world stock indices,” *Physical Review E*, vol. 83, no. 4, p. 046121, 2011.
- [10] L. S. Junior and I. D. P. Franca, “Correlation of financial markets in times of crisis,” *Physica A: Statistical Mechanics and its Applications*, vol. 391, no. 1–2, pp. 187–208, 2012.
- [11] S. Kumar and N. Deo, “Correlation and network analysis of global financial indices,” *Physical Review E*, vol. 86, no. 2, p. 026101, 2012.
- [12] A. Nobi, S. E. Maeng, G. G. Ha, and J. W. Lee, “Random matrix theory and cross-correlations in global financial indices and local stock market indices,” *Journal of the Korean Physical Society*, vol. 62, no. 4, pp. 569–574, February 1, 2013.
- [13] J. Friedman, R. Tibshirani, and T. Hastie, “The elements of statistical learning: Data mining, inference, and prediction: With 200 full-color illustrations,” Springer, 2013.
- [14] C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006.
- [15] Y. Shirota and B. Chakraborty, “Visual explanation of eigenvalues and math process in latent semantic analysis,” *Information Engineering Express, Information Engineering Express*, vol. 2, no. 1, pp. 87–96, 2016.
- [16] G. W. Anderson, A. Guionnet, and O. Zeitouni, *An Introduction to Random Matrices (Cambridge Studies in Advanced Mathematics)*, Cambridge University Press, 2009.
- [17] J.-P. Bouchaud and M. Potters, *Financial Applications of Random Matrix Theory*: Oxford University Press, 2011.

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Kenji Yamaguchi is a lecturer at Science & Education Center (SEC), Ochanomizu University. His research fields are visualization of stock price data, educational technology, and programming education.

From 2010 to 2014, he worked at Computer Centre, Gakushuin University, from 2014 to 2017, he worked at IT Center, Ochanomizu University. And since 2017, he works at Ochanomizu University.

He is a member of Japanese Operations Management and Strategy Association (JOMSA), Japan Society of Business Mathematics, and Information Processing Society of Japan.



Yukari Shirota is a professor of the Faculty of Economics, Gakushuin University. Her research fields are visualization of data on the web, data visualization, social media analysis, and visual education methods for business mathematics. For over 20 years, she has developed visual teaching materials for business mathematics and statistics. She was invited and talked in many tutorials such as one titled “Visually Do Statistical Shape Analysis!” in

DSAA 2017 (Data Science and Advanced Analytics). She organized the special session titled “Awareness computing for economics and social science analysis” in IEEE iCAST 2019 to provide the discussion place on the newest analysis methods.