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Thailand's 2011 Flooding: its Impacts on Japan Companies in Stock Price Data

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ABSTRACT

This paper aims to find which Japan companies whose stock prices were damaged by the flood happened in Thailand in 2011. Many Japanese companies were devastated by the floods. We analyze the matrix of return rates of the largest 225 Japanese stock prices. We proposed the following approach: First, the matrices U, W, and V^T were obtained by using Singular Value Decomposition (SVD) on the standardized form of the return of stock price matrix. Then, two kinds of eigenvectors are introduced: Brand-eigenvector, obtained by multiplying U with W, and Dailymotion-eigenvector, obtained by multiplying S with V^T. Each of them has their own role in the analysis: the Brand-eigenvector decides which company group had been impacted at the time while the Dailymotion-Eigenvector provides solid proof on the decision of the Brand-Eigenvector, showing representative time series fluctuations on the company cluster. The well-known facts that Japan digital camera companies, Nikon, Casio, and Sony, were damaged due to the flood were also used to help the analysis. We use the element of Nikon as the clue to find the damaged Japanese company cluster. By doing these steps, we can identify the correlated clusters of stock return rates. In addition, we utilize Random Matrix Theory (RMT) to identify the random behavior of stock return rates. First, we find the relation between Brand-Eigenvector and cross-correlation matrix eigenvector and between Brand-Eigenvector singular value and cross-correlation matrix eigenvalue. Then, the distribution of the cross-correlation matrix eigenvalues and the elements of all Brand-Eigenvectors are inspected to see their consistency with RMT. By doing so, we are able to see the flood impact on Japanese company return stock rate as a whole for a certain period. In implementation, several tests were conducted. Finally, the Brand-eigenvector #9 was found to be the Brand-eigenvector which best expressed the flood effect on the stock price change at the time, compared with other candidates (Brand-eigenvector #19 and #27). By inspecting the Brand-eigenvector #9, we

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found that the cluster included several Japan companies damaged due to the floods. It was also found that there were similarities, in the stock pattern and decline, between the Dailymotion-eigenvector #9 and the Nikon daily stock price during the last week of September and the first week of October. The dates were the period when the flood damage had intermittently happened owing several typhoons. In addition, through the inspection of the cross-correlation eigenvectors and eigenvalues, we found that the flood damage had a great impact on several Japanese companies during certain period.

1. Introduction

The floods in Thailand in 2011 had damaged several Japan companies. We would like to see the impacts on the fluctuations of their stock prices. Our work aims to detect and analyze the flood impact only from the given stock price data at the time. In order to analyze the impact on the return stock price change, we use the recent results regarding cross-correlations between stocks, namely, methods of random matrix theory (RMT) [1]. Plerou at al. presented their methods and their results on the real stock data in [2]. We apply the same RMT methods with a different the mathematical process. The same eigenvectors can be obtained as their approach. Plerau et al. first calculate the cross-correlation matrix C of stock returns. On the other hand, we start from the return rate matrix of companies. A line of the matrix is corresponding to one company's time series data.

We introduce the Brand-Eigenvector and Dailymotion-Eigenvector approach as mathematical tools. From the eigenvectors, the company cluster of which the stock prices had been impacted by the flood had been detected. The company cluster corresponding to one eigenvector is called Brand-Eigenvector in this paper. We would like to find the Brand-Eigenvector of the flood-damaged company cluster. In addition, in order to utilize the RMT theory explored by Plerou at al., we also look for the relation between the Brand-Eigenvector with the cross-correlation eigenvector and between Brand-Eigenvector singular decomposition and cross-correlation eigenvalue. However, rather than seeing the role of the deviating eigenvectors, we prefer to see the role of Brand-Eigenvector on the return stock price as a whole for certain period.

This paper is written as follows: In Section 2, the Singular Value Decomposition concept in general will be introduced. In Section 3, the concept of Brand and Dailymotion-Eigenvector will be introduced and explained. After that, in Section 4, the relationship between the Brand-Eigenvector and the cross-correlation matrix eigenvector and between Brand-Eigenvector singular values and cross-correlation matrix eigenvalues will be explained. In Section 5, we explain shortly about how the random matrix cross-correlation eigenvectors will be distributed as in [1]. In those explanations, some mathematical notations and terms will be introduced in order to help the readers understand more about the approach used. Next, several tests conducted will be explained: in Section 6, the *Sample Test* using NYSE data is described to help the readers understand more about how our Brand and Dailymotion-Eigenvector approach used in the analysis. In Section 7, the *Small Test* handling of the Nikkei 225 is explained to validate the approach while providing the base of what kind of Brand-Eigenvector being sought. This test, along with *Big Test*, will provide the reader with information on how the flood impacted the return stock market. In Section 7, the *Big Test* to implement the SVD to all Nikkei 225 companies' return stock price change so that we can obtain the flood-affected company cluster. In the last section, some conclusions about the approach and results obtained are summarized.

2. Singular Value Decomposition (SVD)

In the section, we shall explain the math process of SVD [3]. If the target matrix is square, $N \times N$, then we use Principal Component Analysis. But for a non-square matrix, we will use the SDV to obtain the eigenvectors. The visual explanation is represented in [4].

Let X be an arbitrary matrix whose size of $N \times L$. Then, according to SVD theorem, X can be decomposed into several matrices multiplication according to following equation:

$$X = U\,W\,V^T \tag{1}$$

Where U is an orthogonal matrix whose size $N \times N$, W is a diagonal matrix whose size $N \times L$, V is a orthogonal matrix whose size $L \times L$. In addition, If rank of X is $R \leq L$ or $R \leq N$, then matrix W will have $(N - R)$ null rows and $(L - R)$ null columns. A detail explanation about other standard forms of SVD can be read in literature [2].

The matrices U and V^T resulted from SVD decomposition are special matrices. The column vectors of U are orthonormal basis of space spanned by column vectors of X. On the other hand, the row vectors of V^T are orthonormal basis of space spanned by the row vectors of X. The matrix W itself is a diagonal matrix whose entries are zero except, probably, on its diagonal.

In addition, it is assumed that σ_i, the diagonal entries of W and termed as *singular values*, are in ordered fashion so that $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_R \geq 0$. The symbol σ_i shows the importance of its corresponding column vector $\hat{\boldsymbol{u}}_i$ of U (or its corresponding row vector $\hat{\boldsymbol{v}}_i^T$ of V^T) as basis of column space spanned by X (or row space spanned by X in case of V^T). This means the higher of σ_i is then the more important the i^th^ column vector $\hat{\boldsymbol{u}}_i$ is in spanning the column space of X (or the i^th^ row vector $\hat{\boldsymbol{v}}_i^T$ is in spanning the row space of X). It also means that the low σ_i corresponding to low priority of i^th^ column/row vector so that it can be more neglected rather than the higher one in constituting the column/row space of X.

3. Brand and Dailymotion-Eigenvector

In the section, we shall define and explain the concepts of the Brand-Eigenvector and Dailymotion-Eigenvector. In the explanation, we still use similar notation and similar definition of each notation we used in previous section.

First, let right-side multiply X in equation (1) with inverse of V^T. Note that due to its orthogonality, the inverse of V^T is its transpose:

$$X\,V = U\,W\,V^T\,V \tag{2}$$

$$X\,V = U\,W = B \tag{3}$$

$$B = [\boldsymbol{b_1} \quad \boldsymbol{b_2} \quad \dots \quad \boldsymbol{b_r} \quad \dots \quad \boldsymbol{b_R}] \tag{4}$$

The right-side of equation (3) is what we call as *Brand-Eigenvector matrix B* with its column vector $\boldsymbol{b_r}$ as *Brand-Eigenvector*. In addition, let left-side multiply X with inverse of U in equation (1). Also due to its orthogonality property, the inverse of U is its transpose.

$$U^T X = U^T U W V^T \quad (5)$$

$$U^T X = W V^T = D \quad (6)$$

$$D = \begin{bmatrix} \boldsymbol{d_1}^T \\ \boldsymbol{d_2}^T \\ \vdots \\ \boldsymbol{d_r}^T \\ \vdots \\ \boldsymbol{d_R}^T \end{bmatrix} \quad (7)$$

The right-side of Equation (6) is what we call as the *Dailymotion-Eigenvector matrix D* with its row vector $\boldsymbol{d_r}^T$ as *Dailymotion-Eigenvector*.

Let consider again Equation (6) more carefully. Note that the rows of U^T are columns of U. The multiplication of $\hat{\boldsymbol{u}}_i^T$ with the X results in i[th] row of D. It means that each row of D is the linear combination of each row of X as shown in the following Equation:

$$\boldsymbol{d_i}^T = \langle u_1 \rangle_i \hat{\boldsymbol{x}}_{\boldsymbol{1}}{}^T + \langle u_2 \rangle_i \hat{\boldsymbol{x}}_{\boldsymbol{2}}{}^T + \cdots + \langle u_n \rangle_i \hat{\boldsymbol{x}}_{\boldsymbol{n}}{}^T \quad (8)$$

Where $\boldsymbol{d_i}^T$ is i[th] row vector of D^T, $\langle u_n \rangle_i$ is n^{th} element of $\hat{\boldsymbol{u}}_i^T$, $\hat{\boldsymbol{u}}_i^T$ is the transpose of $\hat{\boldsymbol{u}}_i$ which is the i[th] column vector of U, and $\hat{\boldsymbol{x}}_{\boldsymbol{1}}{}^T$ is i[th] row vector of X.

Note that the coefficient parts $\langle u_n \rangle_i$ of the linear combination has a significant role in determining which $\hat{\boldsymbol{x}}_{\boldsymbol{n}}{}^T$ would contribute significantly to the i[th] row of D. The higher the coefficient the more significant its contribution is. The coefficients $\langle u_n \rangle_i$ itself are elements constituting the i[th] column vector of U. The column vectors $\hat{\boldsymbol{u}}_i$ are similar with the column vectors $\boldsymbol{b}_i$ by σ_i factor as shown in Equation (9)

$$\boldsymbol{b_i} = \sigma_i \hat{\boldsymbol{u}}_{\boldsymbol{i}} \quad (9)$$

4. SVD Singular Values and Correlation Matrix Eigenvector Relationship

Before explaining how the Brand and Dailymotion Eigenvectors will be used to analyze the flood impact on the Japan company stock price, the relationship between the Brand-Eigenvector and cross-correlation matrix eigenvector and between Brand-Eigenvector singular values and cross-correlation matrix eigenvalues will be explained. In short, actually, there were literatures [1] which analyze the randomness of cross-correlation matrix by inspecting its eigenvalues which also be the basis of research conducted in this paper. This relationship will be explored first before implementing the Brand and Dailymotion-Eigenvectors.

The cross-correlation matrix C Equation is shown in the Equation (10). Note that it is assumed that the rows of matrix X are in the standardized form.

$$C = \frac{1}{L-1} X X^T \quad (10)$$

By using equation (1), equation (10) can be written as:

$$C = \frac{1}{L-1} (U W V^T)((V^T)^T W^T U^T) \quad (11)$$

$$C = \frac{1}{L-1} U W W^T U^T \quad (12)$$

$$C = \frac{1}{L-1} U \Sigma^2 U^T \quad (13)$$

Because the value of W and W^T are all zero except their diagonals which have value of σ_i, the entries of matrix Σ^2 are also all zeros except for its diagonal entries whose value of σ_i^2.

Next, let multiply both sides with $\hat{\boldsymbol{u}}_i$ as follows:

$$C\,\hat{\boldsymbol{u}}_i = \frac{1}{L-1} U\,\Sigma^2\,U^T\,\hat{\boldsymbol{u}}_i \tag{14}$$

$$C\,\hat{\boldsymbol{u}}_i = \frac{1}{L-1} U\,\Sigma^2\,\hat{\boldsymbol{\imath}}_i \tag{15}$$

$$C\,\hat{\boldsymbol{u}}_i = \frac{1}{L-1} U\sigma_i{}^2\hat{\boldsymbol{\imath}}_i = \frac{1}{L-1}\sigma_i{}^2 U\hat{\boldsymbol{\imath}}_i = \frac{1}{L-1}\sigma_i{}^2\,\hat{\boldsymbol{u}}_i = \frac{\sigma_i{}^2}{L-1}\,\hat{\boldsymbol{u}}_i \tag{16}$$

Equation (14) to Equation (15) step used the fact that U^T has orthonormal row vectors $\hat{\boldsymbol{u}}_i^T$. It makes the multiplication U^T $\hat{\boldsymbol{u}}_i$ will give all zero values except for ith row which result in 1. Meanwhile, the Equation (15) to Equation (16) step used a fact that multiplication of a matrix (in this case Σ^2) with ith column of identity matrix $\hat{\boldsymbol{\imath}}_i$ result in ith column of the matrix. In this case, because the corresponding ith column of Σ^2 has all zero values, except on ith row which has value of σ_i^2, the result is $\sigma_i^2\,\hat{\boldsymbol{\imath}}_i$.

The most important result is described in the Equation (16). From the equation, it can be seen that $\hat{\boldsymbol{u}}_i$ is the *eigenvector* of C with the *eigenvalue* of $\lambda_i = \frac{\sigma_i{}^2}{L-1}$ where λ_i is the cross-correlation matrix eigenvalues and σ_i is the Brand-Eigenvector $\boldsymbol{b}_i$ singular value. It should also be noted that, because Brand-Eigenvector $\boldsymbol{b}_i$ is same with $\hat{\boldsymbol{u}}_i$ with the difference is only by a multiplication factor of σ_i, we can say that the Brand-Eigenvector is also the cross-correlation matrix eigenvector.

5. Eigenvalue Distribution of the Correlation Matrix

The aim of finding the eigenvalue distribution of the correlation matrix C is to extract the randomness property of C. It has been known from literature [2] that a random matrix R of which size is $N \times L$, with N and L are both large enough, and ratio Q of $\frac{L}{N}$ has a probability density function of $P_{rm}(\lambda)$ of eigenvalues λ of its random correlation matrix C is described by [1]:

$$P_{rm}(\lambda) = \frac{Q}{2\pi}\frac{\sqrt{(\lambda_+-\lambda)(\lambda-\lambda_-)}}{\lambda} \tag{17}$$

For λ within the bounds $\lambda_- \le \lambda \le \lambda_+$, where λ_- and λ_+ are the minimum and maximum eigenvalues of C, respectively, given by:

$$\lambda_\pm = 1 + \frac{1}{Q} \pm 2\sqrt{\frac{1}{Q}} \tag{18}$$

In addition, the distribution of elements of the eigenvectors should follow normal distribution equation:

$$\rho_{rm}(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} \tag{19}$$

Though the probability density function of bulk of the eigenvalues is consistent with equation (18), there are some deviating eigenvalues, usually the largest ones or the smallest ones. Those deviating eigenvectors represent influence of the entire market on all stocks. Using these deviating eigenvectors, all stocks studied can be partitioned into distinct subsets whose identity corresponds to conventionally identified business sectors. These sectors are stable in time, in some cases for as many as 30 years [1].

In this paper, rather than using the deviating eigenvectors and their corresponding eigenvalues, the chosen Brand-Eigenvector and their corresponding eigenvalues will be studied to explain the effect of the flood to the stock markets. This is because the flood effect is only happened during a short period so it hardly seems able to influence the stock price as a whole. It is so reasonable that the blood-effected company eigenvector can be found among the non-dominant eigenvectors.

6. Sample Test

To help the reader understand more about the Brand and Dailymotion-Eigenvector approach, a *Sample Test* was conducted. A sample of return stock prices of NYSE (New York Stock Exchange) was used. The representative of seven Japanese companies have been selected just after the great East-Japan earthquake in March 2011. The period is from the first to the last day in March.

By referring to the Equation (1), the entry of matrix X consists of the price change ("return") of stocks i=1,⋯ ,N over a time scale Δt,

$$G_i(t) = \ln S_i(t+\Delta t) - \ln S_i(t) \tag{20}$$

Where G_i is return stock price on ith company and S_i is stock price on ith company.

Since different stocks have varying levels of volatility, the return stock should be standardized:

$$g_i(t) = \frac{G_i(t)-\langle G_i\rangle}{\sigma_i} \tag{21}$$

Where $\sigma_i = \sqrt{\langle {G_i}^2\rangle - \langle G_i\rangle^2}$ is the standard deviation of G_i and the mark $\langle ... \rangle$ denotes the average time over the period studied. The matrix X row vector $\hat{x}_i$ consists of g_i (t) so that the X column consists of g_i on each time t.

The resulting standardized matrix X is shown in Figure 3. The matrix has a size of 7 x 22 which means it contains return stock change data of N = 7 company brands for L = 22 days. The results of SVD operation, which are matrix U, S, V^T, are also shown in Figure (3). Note that the resulting matrix U should have a size of 7 x 7, W has a size of 7 x 22 and V^T has a size of 22 x 22. However, the Rank of the matrix R is 7. It makes W has zero column since 8th column up to 22nd column. For convenience, only a part of W matrix (7 x 7) and V^T matrix (7 x 22) are shown. The parts omitted are not important because it would only result in zero in Dailymotion-Eigenvector.

By using the Equation (3), the Brand-Eigenvector matrix was obtained and plotted as shown in Figure (1b). The plot was obtained by putting the elements of each Brand-Eigenvector $\boldsymbol{b_R}$ and the horizontal axis as the corresponding value of each elements. Different colors are used for different Brand-Eigenvectors such as: red for Brand-Eigenvector #1, yellow for Brand-Eigenvector #2, green for Brand-Eigenvector #3, etc. Here, the symbol "#" denotes the number of the Brand-Eigenvector: the symbol of Brand-Eigenvector #1 means $\boldsymbol{b_1}$, Brand-Eigenvector #2 means $\boldsymbol{b_2}$, etc.

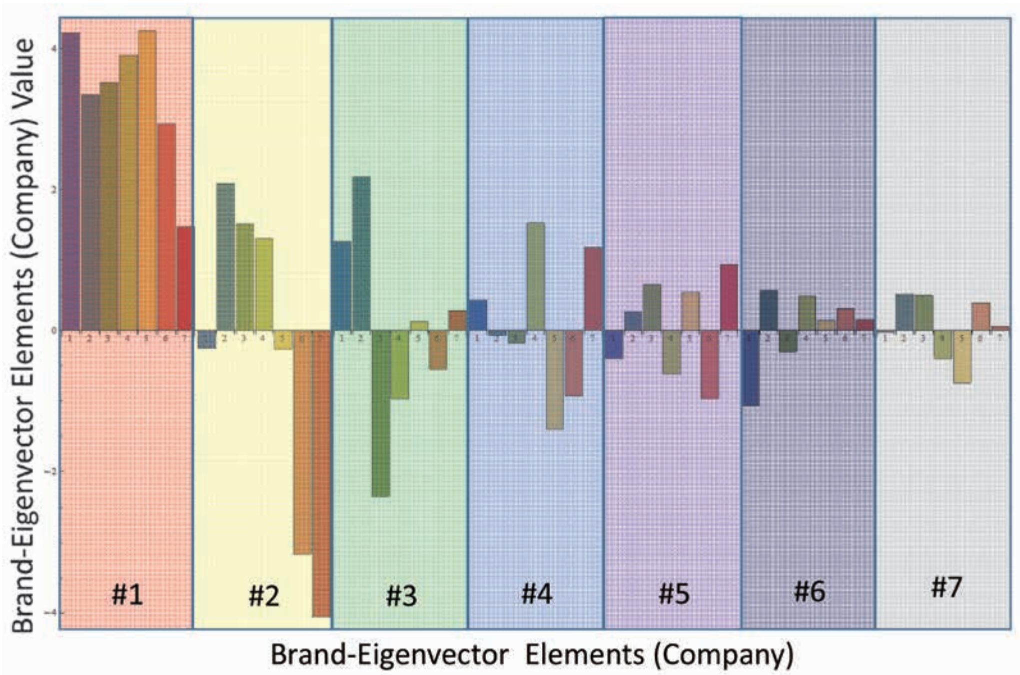
It can be seen from Figure 1 that on Brand-Eigenvector #1, all the elements are positive. In general, the first eigenvector shows the average status. Therefore from this, we can see that all the companies had the same direction movement through the period. By using the equation (6), the accurate Dailymotion-Eigenvector can be obtained. The Dailymotion-Eigenvector #1 illustrates the average fluctuation (See Figure 2 (a)). Figure 2 (a) shows the Dailymotion-Eigenvector #1 and the point data shows the exact average value of all the companies. The exact average point data are similar to the Dailymotion-Eigenvector #1.

Using the similar approach, Brand-Eigenvector #2 was inspected. Note that companies on element of

6th and 7th companies of the Brand-Eigenvector contribute dominantly (See Figure 1(b)). Figure (2b), shows the average of the 6th and 7th companies only. Namely, we focus on the two dominant companies only. By doing so, we found that the daily-motion of the two companies is similar to the Dailymotion-Eigenvector #2.

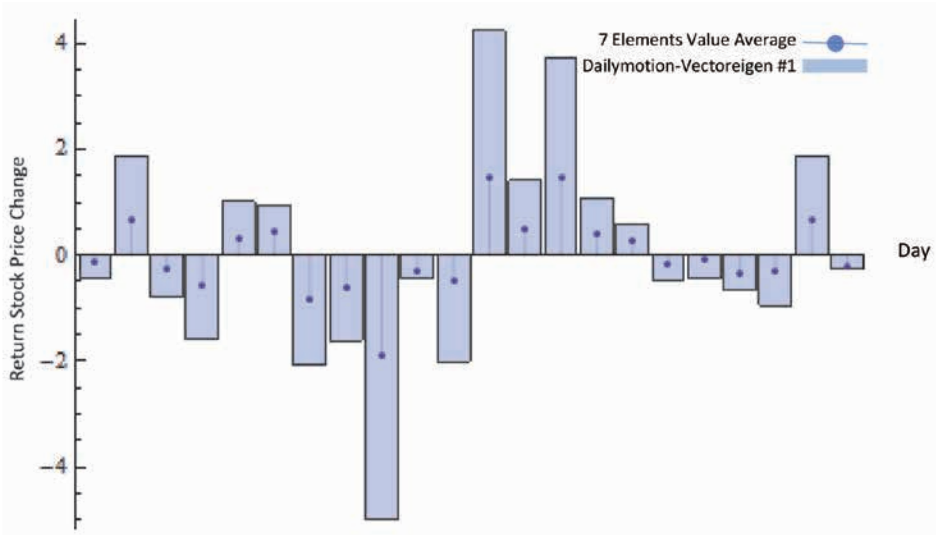
$$B=\begin{pmatrix} 4.22553 & -0.24676 & 1.26227 & 0.43177 & -0.39616 & -1.06938 & -0.0184 \\ 3.34477 & 2.08806 & 2.18731 & -0.0706 & 0.274317 & 0.566581 & 0.516651 \\ 3.51581 & 1.51481 & -2.35251 & -0.17663 & 0.662181 & -0.29414 & 0.503927 \\ 3.90758 & 1.30496 & -0.96011 & 1.52535 & -0.6174 & 0.493114 & -0.39375 \\ 4.25592 & -0.26174 & 0.132904 & -1.39373 & 0.540245 & 0.140189 & -0.73958 \\ 2.92952 & -3.17178 & -0.54851 & -0.93157 & -0.96611 & 0.309949 & 0.399485 \\ 1.46871 & -4.05845 & 0.281936 & 1.17989 & 0.934056 & 0.15402 & 0.063908 \end{pmatrix}$$

(a)

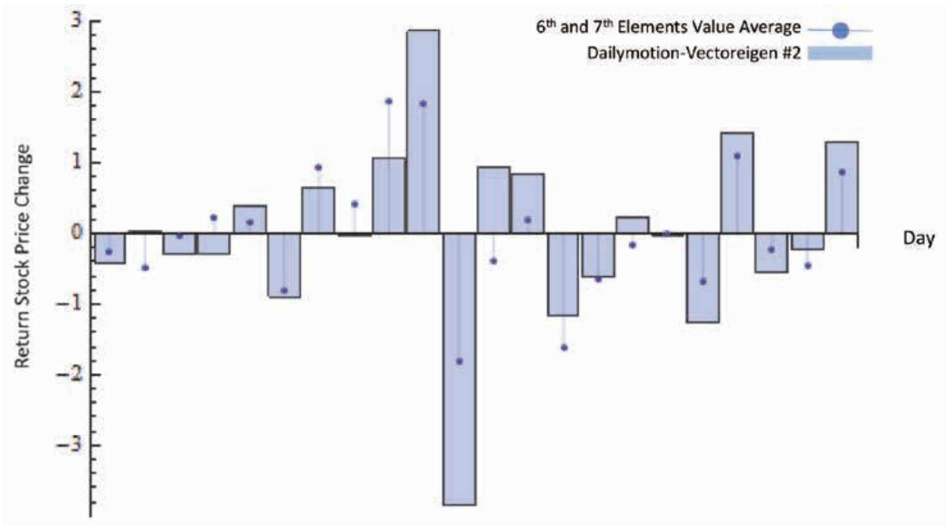


(b)

Figure 1: Sample test of Brand-Eigenvector (a) the matrix B and (b) the plot of each $\boldsymbol{b}_r$. Note that the 1st column is marked as the 1st Brand-Eigenvector #1.



(a)



(b)

Figure 2: Sample test Dailymotion-Eigenvector (a) #1 and (b) #2 Comparison with our approach.

Note that the higher the corresponding singular value is, the bigger impact the Brand-Eigenvector has. In addition, the higher the element (company) in the Brand-Eigenvector is, the more dominant the element (company) contribution in the Dailymotion-Eigenvector and vice versa. This fact is the most important conclusion obtained from the test. This fact will be helpful and used when analyzing the flood impact on the return stock price change data.

7. Small Test

The *Small Test* to see the effects of the Thailand floods was conducted in order to validate the approach of Brand and Daily-Eigenvector when analyzing the return stock price fluctuation. The period is between October 3rd – October 31st in 2011 and the Japanese companies' stock price data were selected from Nikkei 225. The *small test* was conducted for 23 days stock data (resulting in L = 22 days) for N = 10 companies shown in Table 1.

The listed companies consist of automobile and digital camera companies. The listed automobile companies had been damaged in the floods. The digital camera companies that had firms in Thailand had also been damaged: they are Nikon, Sony and Ricoh, although Sony is not in the list now. The listed digital camera companies, however, include companies that had not been damaged of the Thailand floods.

Using same methods as described in *Sample Test*, the plot of Brand-Eigenvector of *Small Test* can be obtained such as shown in Figure 4. It can be seen from the figure that the number of Brand-Eigenvectors is 10. In the Brand-Eigenvector #1, only Nikon has a negative value, although others have positive values. In general, the first Brand-Eigenvector shows the average status of the data like the Nikkei average. Therefore, the negative value of Nikon shows well the Nikon's mediocre performance at the time. In the Brand-Eigenvector #2, Olympus which is a representative camera company in Japan shows the inverse movement compared to the others. The company Olympus was suffered from the scandal then. The Olympus scandal was precipitated on 14 October 2011 and the down fall of the stock prices was not the effects of the Thailand floods. In the Brand-Eigenvector #3, we can see the turndown of Nikon and Olympus, although the turndown reasons are completely different.

Table 1: List of companies used in small test.

No	Company	No	Company
1	Nissan（日産自動車）	6	Suzuki（スズキ）
2	Toyota（トヨタ自動車）	7	Nikon（ニコン）
3	Mitsubishi（三菱自動車工業）	8	Olympus（オリンパス）
4	Matsuda（マツダ）	9	Canon（キヤノン）
5	Honda（本田技研工業）	10	Ricoh（リコー）

$A =$

-0.48031	0.861991	-0.41146	-0.95504	1.09403	0.093206	-1.01226	-0.93714	-2.47336	0.146122	-0.35003	1.6989	0.024423	2.0985	-0.15577	-0.2443	-0.32011	0.074592	0.244319	-0.24851	1.3953	-0.14409
-0.04993	0.934961	-0.51906	-1.17051	0.47387	-0.04255	-0.49961	-0.80024	-1.48233	1.30154	-1.64105	2.10467	0.937149	0.882439	-1.02403	-0.31138	-0.0028	-1.11477	0.619633	0.653558	1.15483	-0.4044
-0.41239	0.551418	-0.09905	-0.35079	0.388358	0.471862	-0.77853	-0.8097	-1.54599	-0.07109	-2.39684	1.67521	1.2544	0.765972	1.23089	1.21536	-0.60412	0.296091	-0.53621	-0.93329	-0.29254	0.980979
-0.46347	0.653721	-0.11978	-0.42678	-0.07523	0.352915	-0.94955	-0.60841	-2.07182	1.03817	-1.70288	1.56174	0.275043	1.88737	0.75436	1.15619	0.348543	-0.64759	0.006819	-1.36942	0.271941	0.128125
-0.12479	0.821025	-0.62469	-0.64773	0.642568	0.509477	-0.72373	-0.35225	-1.99031	-0.9822	-0.72867	2.45617	1.25698	1.23481	0.729195	-0.37089	-0.59218	-0.47093	-0.55979	-0.50525	1.30276	-0.27958
0.766718	0.897075	-0.32884	-0.38801	-0.12436	0.526188	-0.72176	-0.21412	-2.13118	-2.30799	0.850004	0.904554	-0.36558	1.82528	1.15191	-0.17704	0.13708	0.599281	-1.18596	0.134219	0.54664	-0.39409
-0.26037	0.043699	0.408089	-0.0399	-0.2092	1.11648	-1.12197	-0.61387	-1.60927	-1.34293	2.74184	-0.11038	0.006235	1.4295	0.154639	0.502586	-0.10461	0.73426	-0.99236	0.300959	0.329969	-1.36339

$U =$

0.456915	-0.0417	0.347012	0.166167	-0.22323	-0.76902	-0.01563
0.361677	0.352855	0.601314	-0.02717	0.154572	0.407443	0.438707
0.380171	0.255983	-0.64673	-0.06798	0.373124	-0.21152	0.427903
0.422534	0.220521	-0.26394	0.587031	-0.34789	0.354611	-0.33435
0.460201	-0.04423	0.036537	-0.53638	0.304416	0.100813	-0.62801
0.316775	-0.53599	-0.15079	-0.35852	-0.54438	0.222893	0.339217
0.158814	-0.68583	0.077507	0.454081	0.526319	0.11076	0.054267

$W =$

9.24796	0	0	0	0	0	0
0	5.91762	0	0	0	0	0
0	0	3.63756	0	0	0	0
0	0	0	2.59841	0	0	0
0	0	0	0	1.77469	0	0
0	0	0	0	0	1.39058	0
0	0	0	0	0	0	1.17767

$V^T =$

-0.04823	0.204025	-0.08552	-0.17309	0.109237	0.101013	-0.22495	-0.17409	-0.53807	-0.04836	-0.21787	0.457783	0.152126	0.404431	0.115721	0.06265	-0.0514	-0.04763	-0.07095	-0.10303	0.20372	-0.02758
-0.07304	0.005436	-0.04964	-0.04953	0.065249	-0.15049	0.109095	-0.00564	0.179373	0.484219	-0.65184	0.156694	0.143215	-0.19893	-0.10631	0.039374	-0.00692	-0.21418	0.238897	-0.09394	-0.04098	0.219907
0.014291	0.063305	-0.0827	-0.18254	0.126265	-0.10055	0.026905	-0.04132	-0.02173	0.223596	0.2609	0.083648	-0.05782	0.040128	-0.49485	-0.36043	0.037257	-0.19674	0.242972	0.345403	0.353743	-0.27983
-0.24964	-0.10701	0.200283	0.044196	-0.11419	0.091131	-0.20075	-0.17285	-0.14662	0.51865	0.185047	-0.25547	-0.18686	0.274397	-0.14347	0.40586	0.15915	0.005218	0.130482	-0.16932	-0.14044	-0.12787
-0.27359	-0.16059	0.123943	0.024168	0.086387	0.271696	-0.12922	-0.17959	0.098161	0.01774	0.158401	0.126792	0.617971	-0.32017	-0.14108	0.172227	-0.32997	0.035875	-0.11737	0.121822	-0.03609	-0.16738
0.288642	0.08687	-0.00551	0.017386	-0.53444	0.164416	0.032166	0.143047	0.026243	0.027989	-0.05512	0.134856	0.17344	-0.04122	0.041057	0.138605	0.327689	-0.45766	-0.17998	0.130527	-0.11107	-0.34738
0.244909	0.174207	0.067324	-0.19786	-0.06364	-0.0145	-0.05964	-0.30927	-0.11959	-0.04057	-0.23437	-0.12752	-0.04883	-0.02348	-0.19626	0.170542	0.035197	0.332753	-0.058	0.618396	-0.29386	0.144073

Figure 3: Sample matrix *A* and its SVD decomposition result: *U*, *W*, and V^T. Here, only a part of *W* (7 x 7) and V^T (7 x 22) are shown.

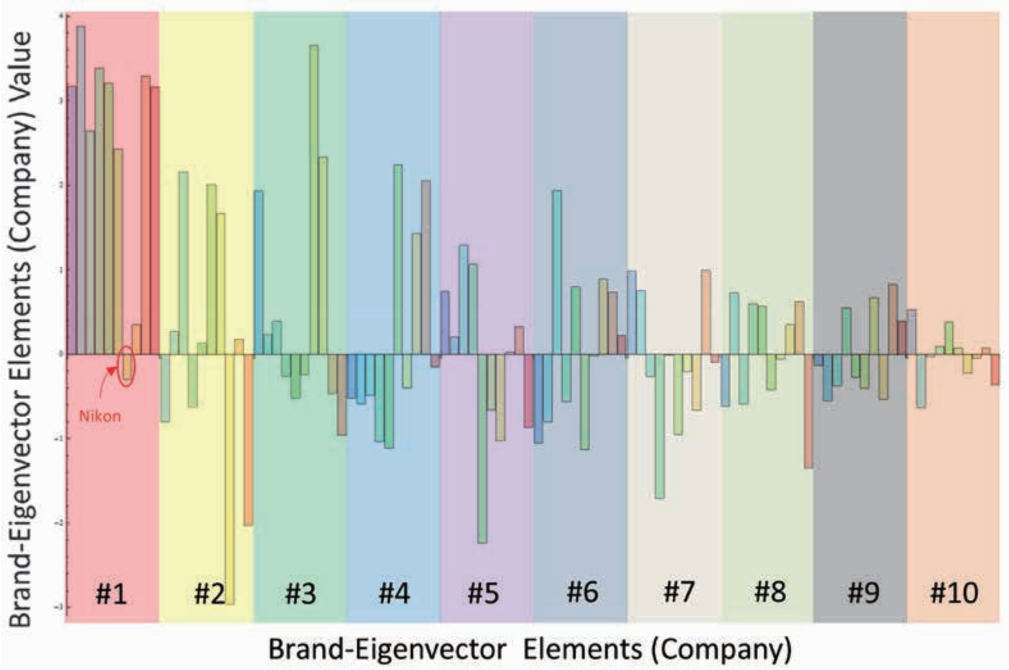


Figure 4: Small test Brand-Eigenvectors.

Let further examine the eigenvectors by seeing their consistency with random matrix $P_{rm}(\lambda)$. It can be seen from Figure 5 that the largest eigenvalues deviate from the $P_{rm}(\lambda)$ but the others are consistent. It is a bit surprising that a small size matrix (where N and L are small) still fit with the $P_{rm}(\lambda)$ curve. Other important fact is that, by inspecting only several companies for two weeks during the flood happened, we found that the Brand-Eigenvector which best expressed the flood impact is the most dominant Brand-Eigenvector (Brand-Eigenvector #1) in term of its singular values. It means that the flood had impacted those several companies' return stock price change significantly during the period when it happened.

8. Detection of Eigenvalues on Nikkei 225 Data

In order to detect the Eigenvalues on Nikkei 225 data which are the most representative Japan's companies, the *Big Test* was conducted. We set the number of companies $N = 200$. The period is during September 1st - December 22nd which includes 81 days (resulting in $L = 80$).

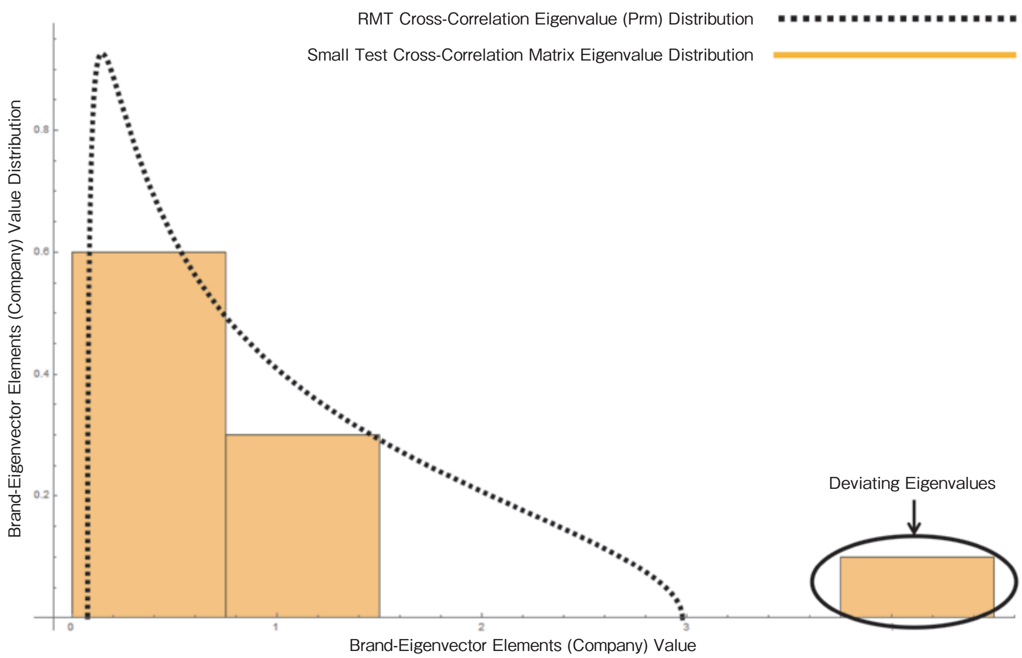


Figure 5: Cross-Correlation matrix Eigenvalues distribution of the small test.

We know from other sources such as newspapers and so forth that Nikon Company was most severely damaged by the flood among the three digital camera companies. Therefore, we will look for the Brand-Eigenvector which best expresses the feature of the Nikon Company return stock price change. Then we can expect that the Brand-Eigenvector found would also show other flood damaged companies among all the companies in the list. In order to do so, first we collected every Nikon element factors of each Brand-Eigenvectors and plotted that in Figure 7. In the plot figure, we found the three most negative ones (See the marked ones in Figure 7): they are Brand-Eigenvector #9, #19, and #27.

As shown in Figure 6, the Nikon Company has its biggest absolute values on Brand-Eigenvector #9, Brand- Eigenvector #19, and Brand-Eigenvector #27. In our interpretations, it has no sense whether the value is negative or positive. Only the impact factor magnitude is significant. Therefore, a negative value does not always express a downfall of stock prices.

The eigenvalues of Brand-Eigenvector #9, #19, and #27 are σ_9=316.61289, σ_{19}=12.50825, and σ_{27}= 10.89382 respectively. Among them, the eigenvalue of the Brand-Eigenvector #9 is the largest one (which means the corresponding singular value is also the largest one) and would be more dominant compared to the other two Brand-Eigenvectors. Then, a deeper inspection on the three Brand-Eigenvectors were conducted.

Let us see the element of Brand-Eigenvector #9 in Figure 7(a). There included many flood damaged companies. The brand of which the return rate is less than minus 1.5 are selected. The number of them is 20. In addition, we selected flood-damaged companies. Among the brands with return rate less than minus 1.5, the flood damaged companies were extracted using the flood damaged company list [5].

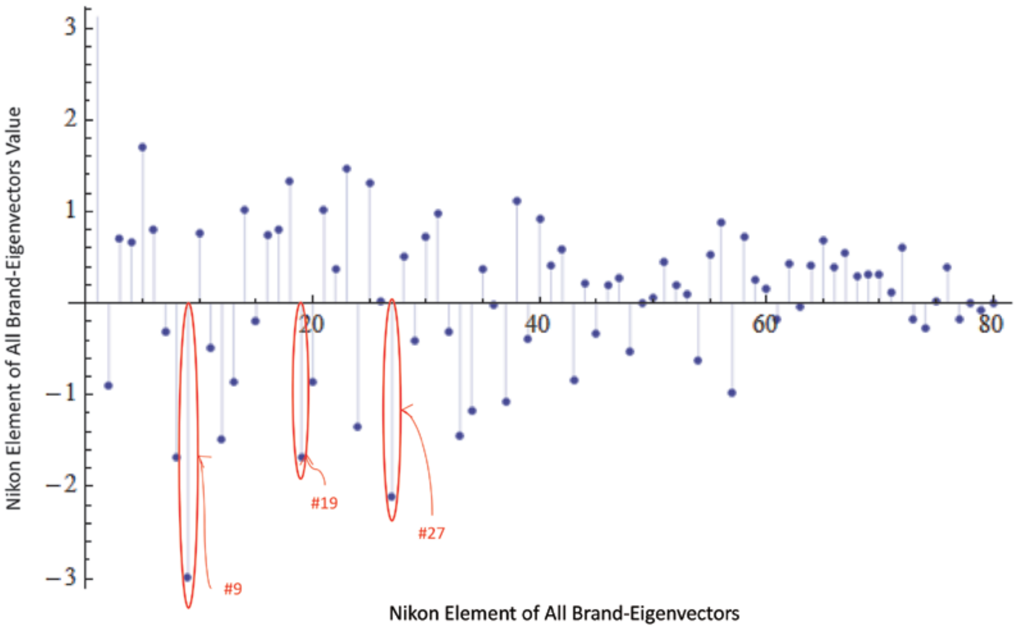
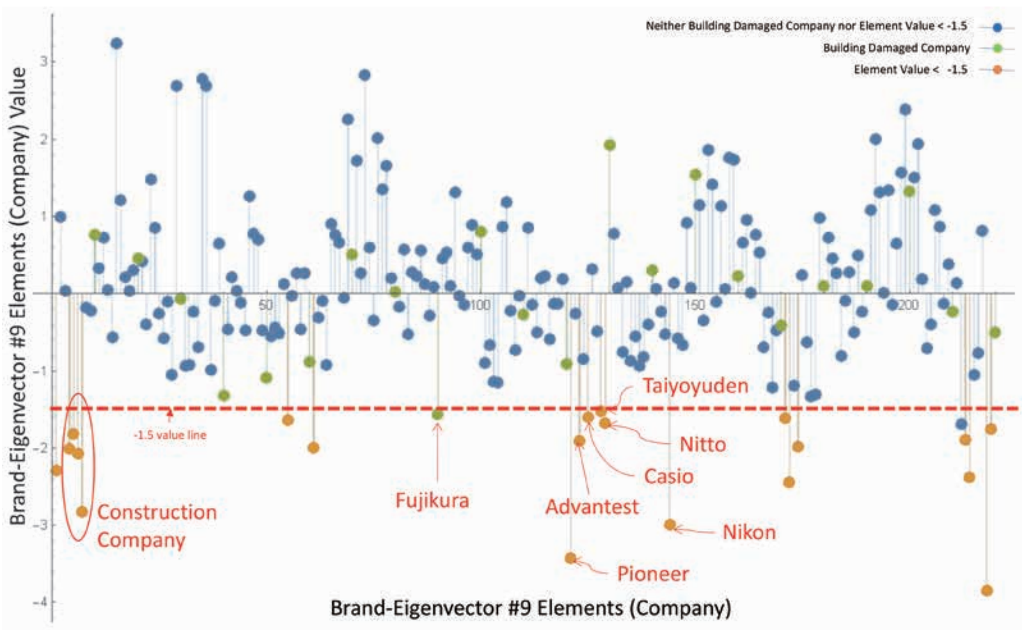
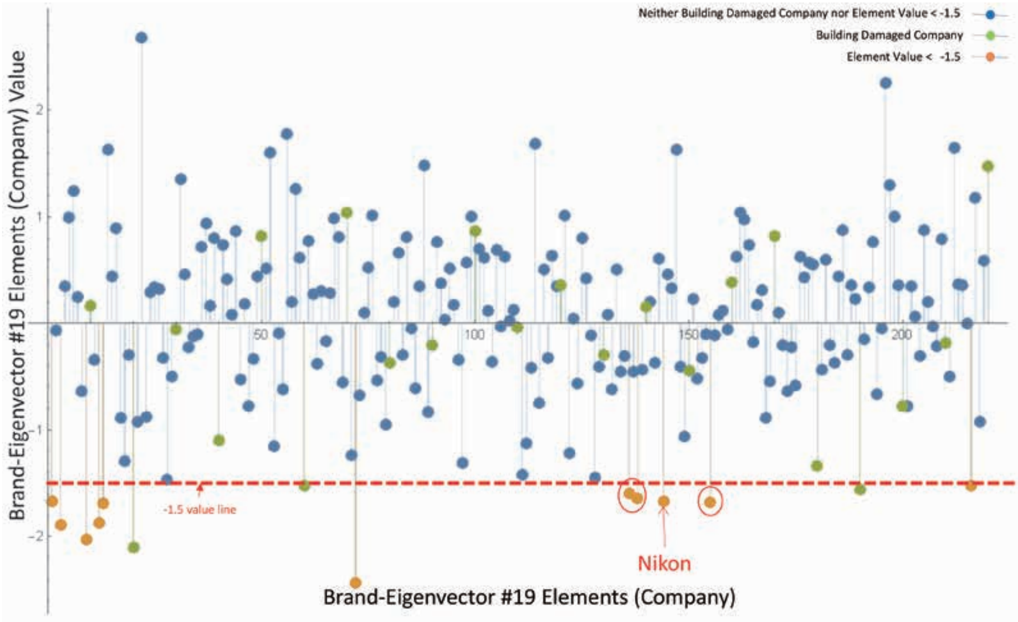


Figure 6: Nikon element impact factors among all Brand-Eigenvectors.

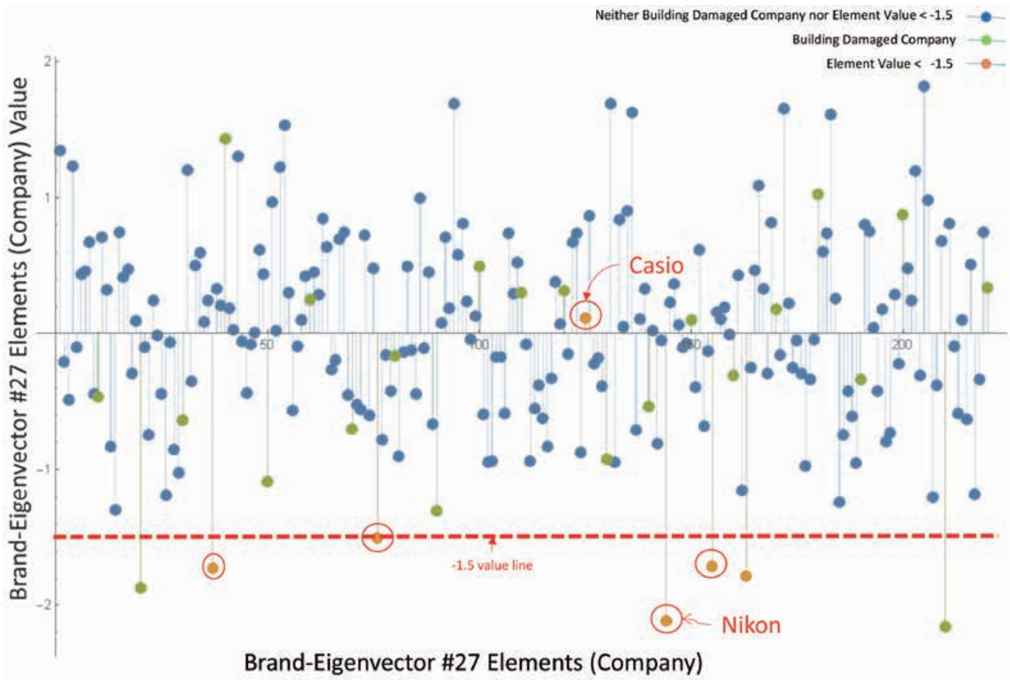


(a)

Figure 7: Brand-Eigenvector (a)#9, (b)#19, and (c)#27.



(b)



(c)

Figure 7: Brand-Eigenvector (a)#9, (b)#19, and (c)#27.

As a result, seven companies which included Nikon and Casio were found. The worst was Pioneer (See Figure 7(a). Surely, Pioneer had been affected a lot of by the floods. The construction company group such as Kashima and Shimizu was also found in the eigenvector as the one with considerable negative values (See the left side of Figure (7a)). The companies have some relationship to Thai concerning the Thailand flood-control plans. So maybe the flood may also have damaged the companies. But, the reason of the construction companies' declines in the eigenvector has not been clarified. We will continue to find the real reason of their declines.

In Brand-Eigenvector #9, among the 20 brands, 8 brands are found to be the flood damaged companies. This means that the ratio is 35 %. In addition, the Nikon and Casio element values are considerable negative ones. Therefore we may interpret the Brand-Eigenvector #9 to be the one which expresses the flood effects on Japanese companies including Nikon.

To provide more solid proof about it, let us see the other Nikon featured brand-eigenvectors, #19 and #27 (See Figure 8 (b and c)). In the Brand-Eigenvector #19, 14 brands have the negative value lower than -1.5 and among them the flood damaged companies are four brands including Nikon and not Casio. The ratio is 29 % and lower than Brand-Eigenvector #9.

Meanwhile, in the Brand-Eigenvector #27, seven brands have the negative value lower than -1.5. There are four flood damaged companies (which have Nikon and but exclude Casio) among them. The ratio is 57% and bigger than the #9 ratio 35%. However, there Casio value was positive in the eigenvector.

Before deciding that the Brand-Eigenvector #9 as the eigenvector that best represents the effect of flooding in Thailand on the Japan companies' stock change, let us proceed to see the Dailymotion-Eigenvector #9. We determine there are similarities between the Dailymotion-eigenvector #9 and the Nikon return stock price change. These comparisons can be seen in Figure 9.

The flood damages had intermittently happened due to several typhoons during the end of September to the beginning of October. On the return rate change of Nikon, the large decline can be seen on 29th September and on 3rd October. During the period, the large decline were also found in the Dailymotion-eigenvector #9. The eigenvalues are shown in Table2.

Table 2: Eigenvalues of #9, #19 and #27. $\lambda = \frac{\sigma^2}{80-1}$.

Brand Eigenvector No	Brand Eigenvector eigenvalue σ	Cross Correlation Matrix C eigenvalue λ
#9	16.61	3.49
#19	12.51	1.98
#27	10.89	1.50

By inspecting Figure 8, lets examine the cross-correlation eigenvalues to see whether they are consistent with $P_{rm}(\lambda)$ or not. It can be seen From the Figure 9 that the two largest eigenvalues deviate from the $P_{rm}(\lambda)$ bounds, which fall within $\lambda_{-}=0.433375 \le \lambda \le \lambda_{+}=7.06662$, but the rest are consistent with the $P_{rm}(\lambda)$. Note that the eigenvectors for Brand-Eigenvectors #9, #19, and #27 are all fall within the $P_{rm}(\lambda)$ curve which makes them as a "random" data. This result is different from the result obtained

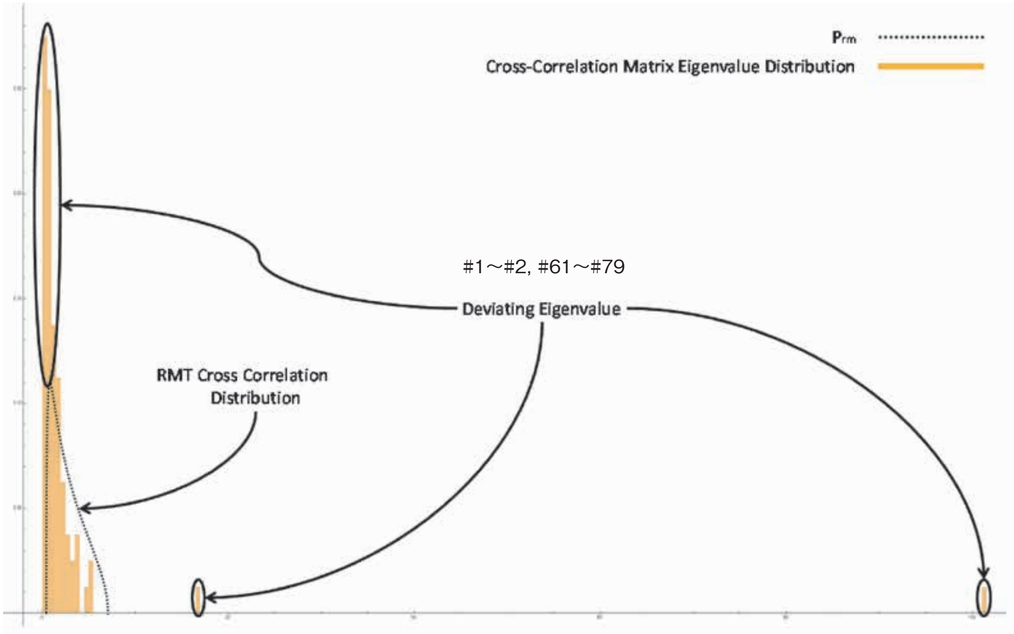


Figure 8: Cross-Correlation matrix eigenvalues distribution.

in *Small Test*. The reason for this is because the flood only gave impact in short period (about two weeks), compared with two months period recorded. In addition, not all companies from the 220 companies listed were impacted by the flood. It makes the flood impact looked like "random" effects in the return stock price change data.

Further, let us take a look at the eigenvector elements histogram curve as shown in Figure 10 and 11. It can be seen that for $\boldsymbol{b}_1$～$\boldsymbol{b}_2$, and $\boldsymbol{b}_{61}$～$\boldsymbol{b}_{79}$ the distribution of elements of the Brand-Eigenvectors are not consistent with the Normal Distribution.

The random matrix eigenvalues are $\lambda_- = 0.433375 \le \lambda \le \lambda_+ = 7.06662$ (See Figure 8).

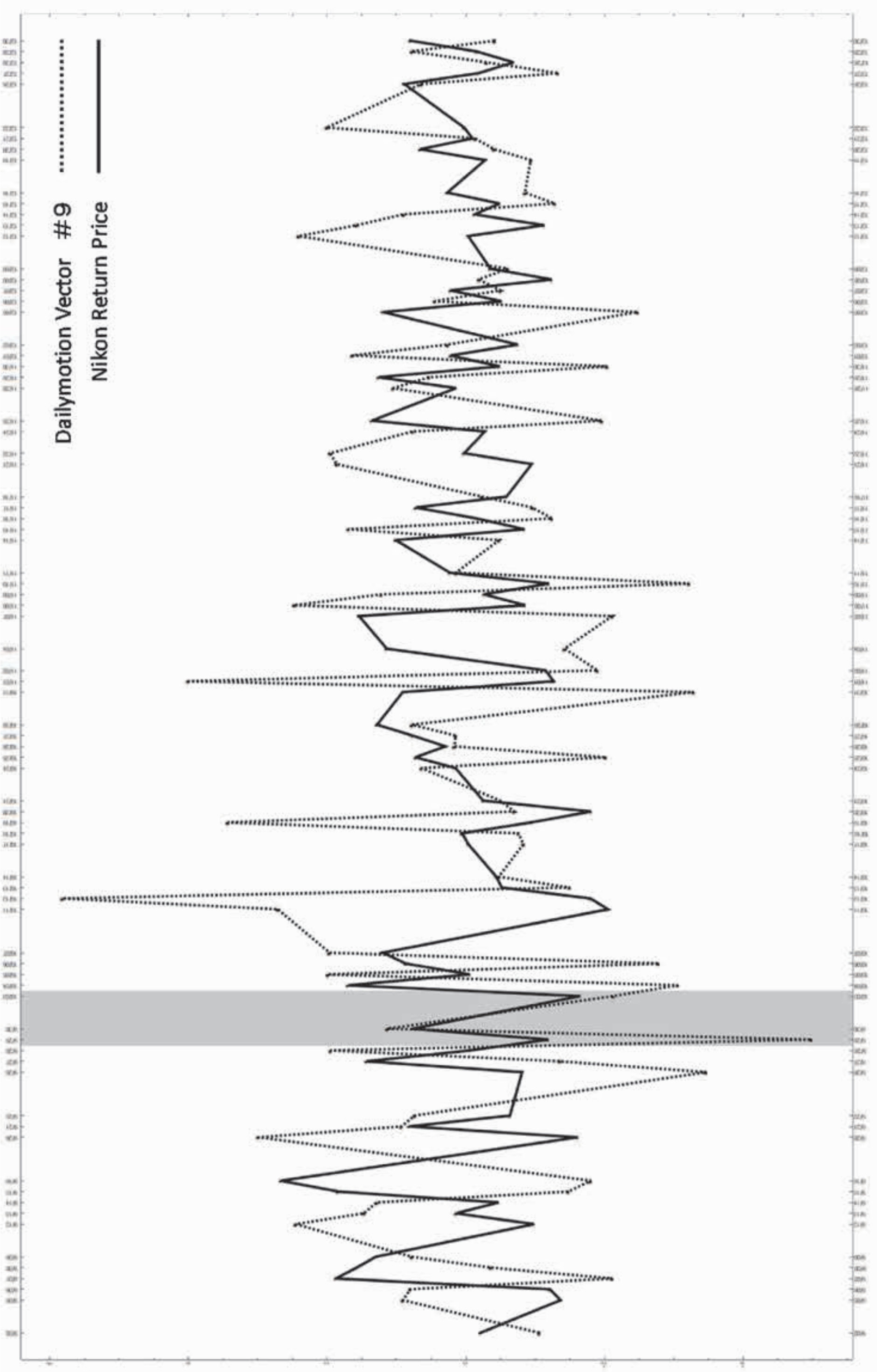


Figure 9: Comparison between Dailymotion-Eigenvector #9 and Nikon return stock price fluctuation.

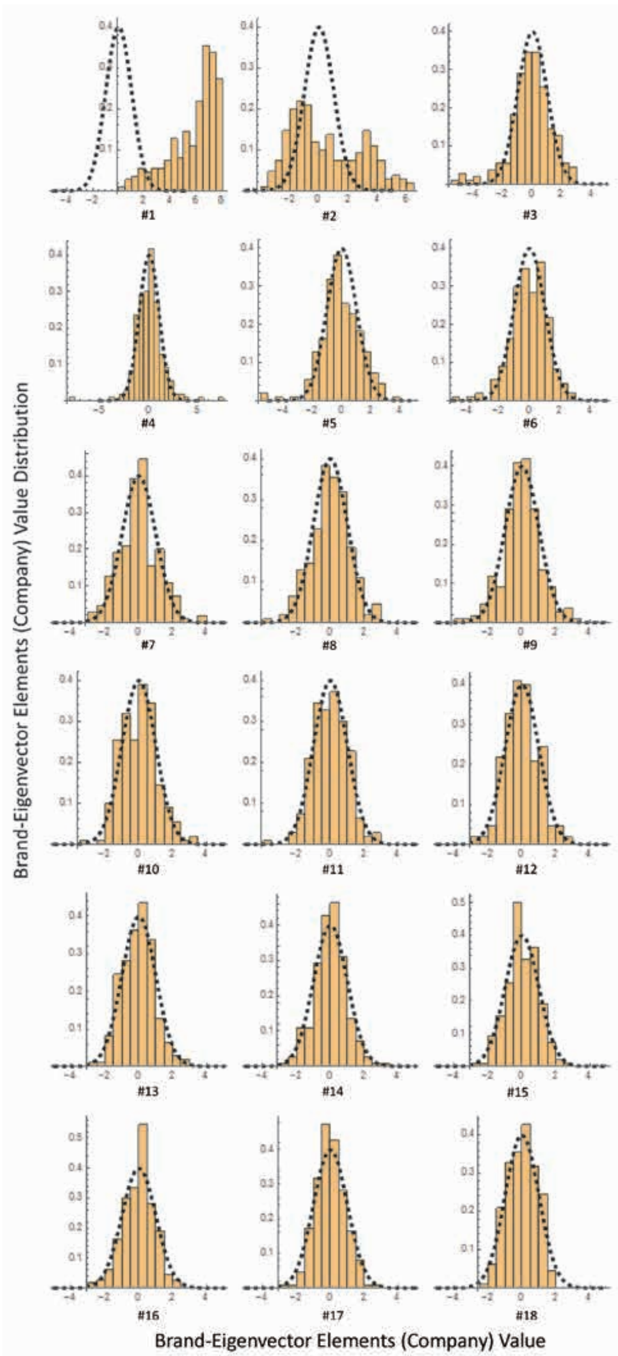


Figure 10: Distributions of elements of Brand-Eigenvectors $\boldsymbol{b}_1$-$\boldsymbol{b}_{18}$.
The dotted line shows the Porter-Thomas distribution for the random matrix.
In the figures, #1 and #2 distributions show non-random, attributes.

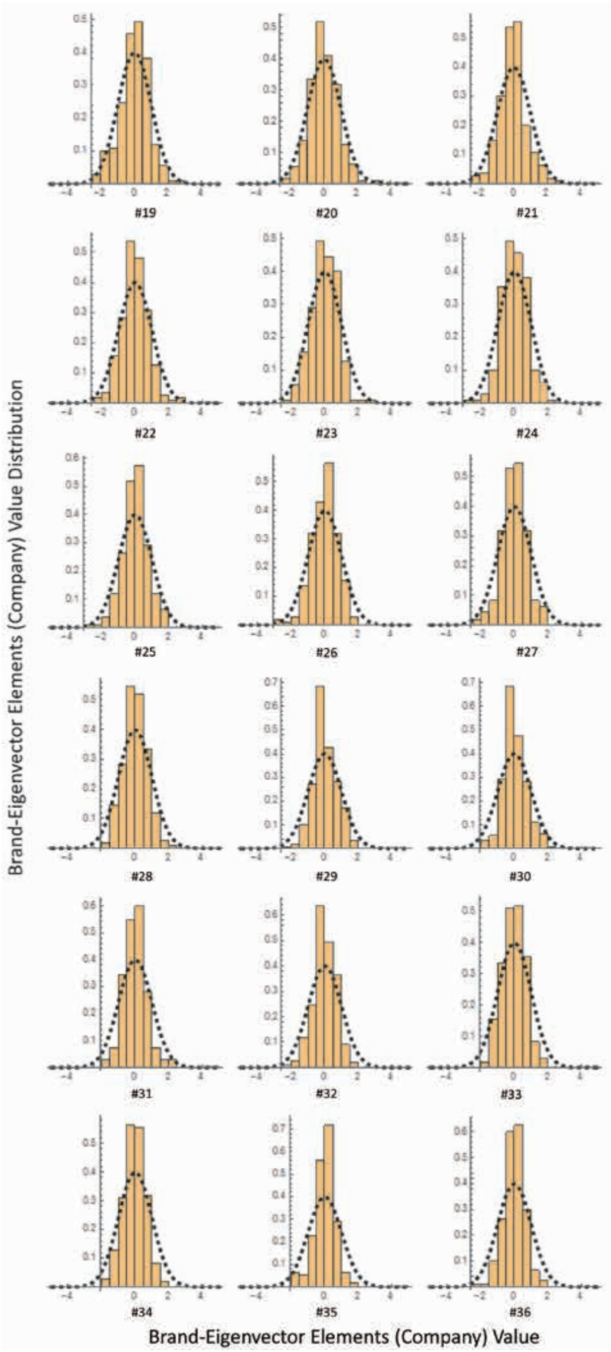


Figure 11: Distributions of elements of Brand-Eigenvectors b19-b36.

9. Conclusion

Many Japanese companies had been damaged by the Thailand floods in 2011. In order to analyze the impact of the flood on the stock price data in this research, we used the Brand and Dailymotion-eigenvector approach. We first made the company-daily return rate data matrix, using Nikkei 225 stock data. The period is during September 1st - December 22nd which includes 81 days.

The well-known fact that several digital camera companies, such as Nikon, Casio, and Sony, had been damaged due to the flood was also utilized in the searching. In addition, the distribution of cross-correlation matrix eigenvalues and the Brand-Eigenvector elements were also inspected to see its similarity with $P_{rm}(\lambda)$ and the Normal Distribution curve, respectively.

Several tests are implemented before finding the Brand and Dailymotion-Eigenvector on the real target data. The *Sample Test* was used to give an explanation about how the Brand and Dailymotion-Eigenvector approach works. Then the *Small Test* was conducted to validate the approach. In this test, it was found that Nikon Company was severely damaged due to the flood. In the *Big Test*, we used the about 200 companies' stock data from Nikkei 225. From the resultant Brand-Eigenvectors, we selected three Nikon featured Brand-Eigenvectors. Then they which were #9, #19, and #27 were inspected in detail. In the end, it was decided that Brand-eigenvector #9 best expresses the flood impact, compared with other possible Brand-eigenvector candidates (#19 and #27). The comparison was done by considering additional well-known facts and their corresponding *singular values*. It was found that the Brand-eigenvector #9 showed strongly several flood damaged companies. The decline of Pioneer was shown largely there which is well known as the flood-damaged company. Therefore we can say that the Brand-eigenvector #9 shows an impact status by the flood damage on the stock data.

Plerou et al. used the cross-correlation matrix to find the stable company cluster for the portfolio making. On the other hand, we have used the eigenvectors of the cross-correlation matrix to find the sudden impact factor of the disaster damage. As our future work, we would like to invest the continuance duration of the impact of the company cluster.

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