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Impacts of US-China trade friction on stock prices: An empirical study of machinery companies

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ABSTRACT

The address by President Trump on the trade between US and China in May, 2019 had a significant and global influence on manufacturing companies. In this paper, we extracted the stock price decline patterns due to the address by using Singular Value Decomposition Method with the intention of introducing a new approach to measure patterns of effects of such contingencies which happen once in a while on stock prices. The results are expected to have also meaningfulness for investors as well as analysts. Our analyses include two types. The first analysis focuses on the extraction of patterns among companies which have high intensity of business engagement in China and the second one among counties. In the first analysis we used only Japanese companies' data because of data availability. As to the second analysis, we used only machinery industry's data of Germany, Japan and US which compete in the global market and have mature stock markets respectively. The analyses made differences of patterns among businesses such as B-to-B and B-to-C stand out in the first analysis and differences among countries in the second analysis. Those results are expected to inspire further research, especially, exploration of new methodologies in the area of analysis of stock price fluctuations due to economic crises such as global trade or political affairs.

Keywords: Disastrous impact on stock prices, US-China trade friction, Singular value composition.

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1. INTRODUCTION

In the Tokyo stock market on the 7th, May, 2019, the decline of stock prices in the industries susceptible to economic conditions such as electrical equipment and machinery was noticeable (from Newspaper Nikkei 2019/05/08). The trigger of the decline is that on May 5, 2019 President Trump stated that the previous tariffs of 10% levied on \$200 billion worth of Chinese goods would be raised to 25% on May 10 (Office of United States, 2019). The President's remark had a significant negative influence on almost all of manufacturing companies around the world. We can expect that the trade friction between the USA and China would give a great risk to most of companies. Especially manufacturing companies which are involved in Chinese economy or market to some extent would be given a negative influence accordingly.

In the paper, we hypothesize that there could be certain patterns of stock price movements as a whole, though we can estimate that many peculiar factors such as individual properties of companies perceived by investors and investors' speculation work on the stock prices. At least, we did confirm the general decline of stock prices. Then we confine ourselves to extract such patterns firstly in this study. Extracted such patterns are expected to give certain meanings to investors as well as companies when they try to optimize their investment or business portfolios. As the second aim of this study, we try a methodological adventure by using Singular Value Decomposition Method to find the stock price movement patterns among the manufacturing companies at the trading conflict. The stock price data we use are those of Japanese, US and German machinery companies. We made analyses of two cases, firstly for only Japanese companies to control the degree of involvement of companies in China and secondly for three countries' companies to control nationality.

In the next section, we explain the method we used. Then in section 3 the results of the first analysis and in section 4 the results of the second analysis will be shown. Then in section 5, we review the results and conclude this study.

2. STOCK MOVEMENT ANALYSIS

In this section, we describe the method for this study. The analysis method we used is a clustering method called Singular Value Decomposition method (Hereafter, SVD) (Friedman et al., 2013; Bishop, 2006). In the financial engineering, the problem of portfolio optimization is one of the most important issues. The essence of the optimization is to combine various groups each of which is characterized by identical stock price movement under specific optimization strategy. Then our study is expected to contribute to identification of such specific patterns. In this study, however, we only exemplify one approach to extract such patterns using stock price changes in the trade friction case. The objective of this analysis is to extract similar stock price movements. This is a kind of the unsupervised learning. There are typically two approaches, clustering and factor analysis (Kolanovic and Krishnamachari, 2017). For example, K-means (Koutroumbas and Theodoridis, 2009) and hierarchical clustering are clustering methods used in the portfolio problem (Lee et al., 2010; Konstantinov et al., 2020; Raffinot, 2017). Concerning the portfolio optimization problem, historical analyses have shown that Hierarchical Risk Parity (Prado, 2018; Prado, 2016) which uses a hierarchical tree clustering have been confirmed to outperform standard approaches (like maximum Sharpe Ratio Portfolio by Markowitz (1952)) (Kolanovic and Krishnamachari, 2017; Prado, 2020). Another approach is the factor analysis. A typical factor analysis is Principal Component Analysis (Hereafter, PCA) and SVD (Bishop, 2006; Koutroumbas and Theodoridis, 2009). PCA and SVD are a family of dimensionality reduction method and extracted principal components represent main drivers of the data variation (Kriegel et al., 2018; Granato et al., 2018). In this paper, SVD method is used to extract company groups each of which has similar movement of stock prices. An eigenvector of the sampled companies hereafter, **GRP** notifies a principal component of the time series data of stock prices (Shirota and Chakraborty, 2016).

The input data of SVD consist of standardized return values calculated from the stock price data (Plerou et al., 2000; Anderson et al., 2009; Bouchaud et al., 2011). A return value is a natural logarithm of the ratio of today' stock price to yesterday's one and defined as follows:

$$\boldsymbol{G_{i,j} = ln(S_{i,j}/S_{i,j-1})}$$

where,

$\boldsymbol{S_{i,j}}$: i-th company's stock price on j-th day, and

$\boldsymbol{G_{i,j}}$: the return value on j-th day of the i-th company.

The size of standardized data matrix named X is **N (companies) × T (days).** When the data matrix **X** is given**,** the SVD process outputs three matrices **U, W, V$^{\mathbf{T}}$** (See Fig. 1). **The r eigenvectors of UW are principal components**, where **r** is the rank of X as shown in Fig. 1. A principal component consists of N elements, that is, the sampled companies (See Fig. 2). The first principle component explains the largest part of the data variation.

A principal component (eigenvector) consists of N company elements. As shown in Fig. 2, each company element' coefficient value is positive or negative. In Fig. 2, almost all companies' coefficient values are negative. Let us define the notation. In the paper, we notify a principal component by "GRP#[number]" such as GRP#7 which means the seventh principal component. Furthermore, if we write GRP# +7, it means signs of coefficient values of representative elements (companies) of this principal component are + (positive). The representative companies are chosen by a cut-off value set by the analysts. In the case of GRP#-7, the representative companies' coefficients are – (negative). In Fig. 2, we set the cut-off value of 2.0 to select the group's representative companies with less than -2.0 in their coefficient values. The number of such representative

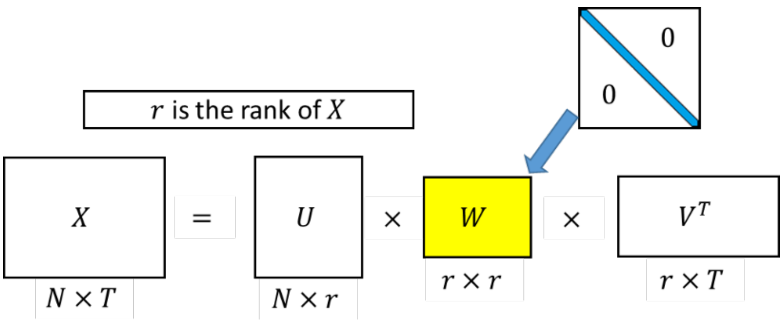

Fig. 1. The output of SVD is the input matrix X and the output is three matrices, U, W and V

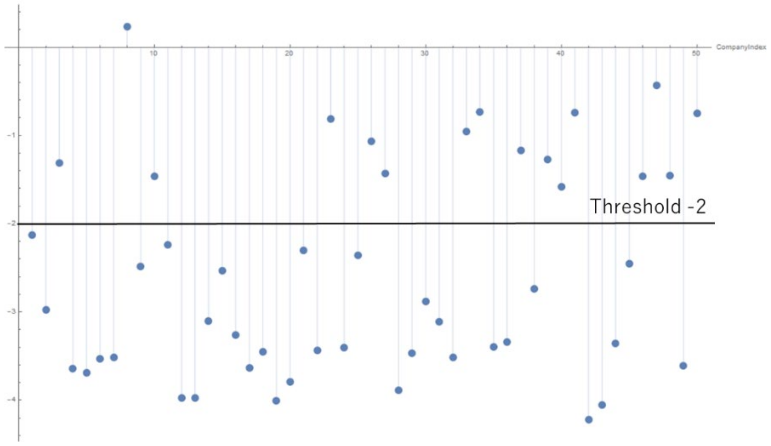

Fig. 2. The GRP#1's N (= 50) element values. The threshold level is set to be -2.0

companies in Fig. 2 is 34. We need to decide the threshold level appropriately because we interpret the component's meanings or characters based on such representative companies' properties. Usually the threshold levels range from 1.5 to 4 from such consideration. Too few may lead to too intrinsic factor-depend implications and too many to too general factor-depend ones.

Our target is the short period after the remark of President Trump. When observing the stock price plunge after the address, we are inclined to grasp comprehensive declining patterns, those of specific companies or a set of such companies and be inquisitive about underlying factors of such patterns. When identifying any patterns in the data, we used to resort to PCA. Principal components of PCA show us clusters each of which has unique having similar movement. In this paper, we use the principal components by SVD instead of PCA, because our input data set is a N x T rectangularly formatted data.

3. JAPANESE MACHINERY INDUSTRY

In the section, we will analyse 50 Japanese companies by SVD. These companies are classified as "Nikkei China-related stocks" by Nikkei and listed in the first section of the Tokyo Stock Exchange Market. The companies are actively involved in the business with China. Therefore, the impact of the trade friction would be large. Our research concern is whether the effects of the trade friction matter in terms of business type. The size of this sample was determined from the convenience of handling as the trial purpose. The data period is from 2019/04/25 to 2019/06/04 of which business days are 23 days. Firstly, let's see the result of SVD in Fig. 3. To visualize the result, we draw the impact network assuming the drawing starts with a company of interest to researchers (in this case, FANUC, a manufacturer of numerical control machineries, is set as the starting company) and the depth parameter 2 (the number of principal components picked up usually based on the degree of explanatory contribution, in this case, two principal components), and the threshold level 2.0. As to the choice of cut-off values we discuss below again. We set a company of interests for researchers at the starting position (the company of origin). The drawing starts from the company of origin. The drawing algorithm works as follows:

1. Set the input matrix and execute SVD.
2. Find the representative companies of GRPs (principal components) together with the company of origin and draw a network around the company of origin for each GRP. A company may belong to several GRPs.
3. For each GROUP among the above-mentioned GROUPs, find the representative companies and draw the graph of the GROUP while the depth from the origin is smaller than the given depth parameter such as 2.

The impact network in Fig. 3 is our original visualization of the principal components structures consisting of the representative companies extracted from the dimensionality reduction method. There is no special theory about that, and the theory behind the impact network is clustering by PCA/SVD.

In Fig. 3, GRP# -1 (Group No. 1, the first principal component, of which member companies have negative and smaller, or larger in the absolute value, than the cut off value -2.0) and GRP# +2 (component companies are selected following the same way as explained above in parenthesis besides the cut off value 2.0) represent the first and second principal components' structures in terms of company respectively.

Fig. 3 indicates the choice of cut-off values is worthy of adequate consideration. Based on our experiences of using SVD, the cut-off value could range from 1.3 to 4. But there is no theory supporting it. In fact, Fig. 3 shows "Seven & I" (a holding company comprises Seven-Eleven, the largest convenience store retailer in Japan, as a business) has two features of GRP# -1 and GRP#2. If the cut-off value is changed from 2.0 to 2.7, the link from "Seven & I" to GRP# -1 does not exist. To investigate the relationship among the groups, we move the threshold level and find the network changes, so that we can find the interesting relationship.

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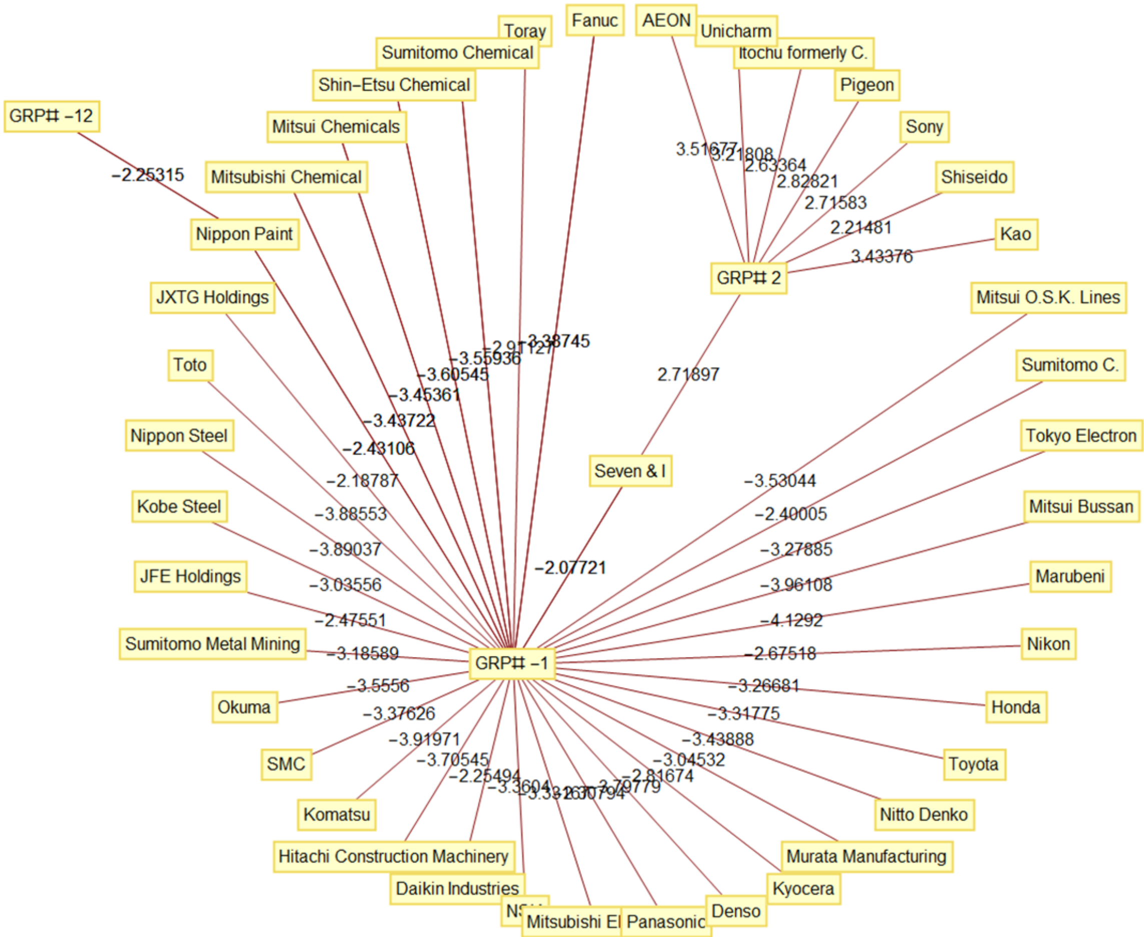

Fig. 3. Impact network of the period 23 days (2019/04/25 to 2019/06/04)

In Fig. 3, we found that some differences between the two groups, GRP# -1 and GRP# +2. The former group consists of mostly manufacturing companies and some large trading companies join in this group (See Table 1). On the other hand, companies in the final consumer goods business such as large retailing, cosmetics and diapers occupy the second group, GRP# +2. Seven and I Holding company has a unique property covering the two groups. Comparing these two groups suggests, beside the difference of market such as B-to-B (high percentage of the companies of Group# -1) and B-to-C (most of the companies of Group# +2), the companies belonging to GRP# -1 are considered more committed in China market in terms of history as well as resources such as capital commitment. The differences in these aspects make us estimate the effects of the trade friction would be more significant to the companies of Group# -1 than those of Group # +2. The confirmation of this estimation can be derived from the coefficient values of the principal component. Those of Group # -1 are generally larger than those of Group# +2 in terms of the absolute term.

Table 1. GRP# -1 top 20 representative companies' industry kinds and the element values

Industry Category	GRP# -1
general trading company	-4.2
general trading company	-4.1
machinery company	-4.0
steel company	-4.0
toilet manufacturing company	-4.0
electric manufacturing company	-3.9
machinery company	-3.8
chemical company	-3.7
chemical company	-3.6
machinery company	-3.6
shipping company	-3.6
chemical company	-3.5
electric manufacturing company	-3.5
chemical company	-3.5
electric manufacturing company	-3.5
machinery company	-3.5
machinery company	-3.4
electric manufacturing company	-3.4
automaker	-3.4
wholesale business company	-3.4

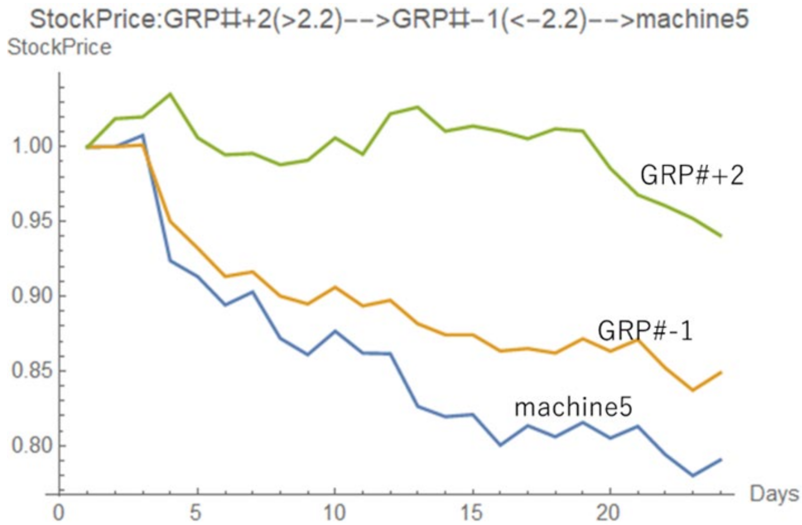

Fig. 4. Stock price movement of each group's representatives in Nikkei China-related 50 companies

Fig. 4 shows the transitions of stock price indexes calculated based on the sums of stock prices like Dow-Jones average of the constituent companies of the two groups. The cut-off values are 2.2 (for Group# +2) and -2.2 for Group# -1. In addition, that of the top 5 machinery companies of GRP# -1 is put together. X-axis shows the days and Y-axis the sum of stock prices with the first day being set as 1. We can spot the difference between curves' shapes of GRP# -1 and GRP# +2. The curve of GRP# -1 decreased from the beginning. That of GRP# +2 was modest compared to the GRP# -1. The top 5 machinery companies' average stock price plunges as soon as the address. These lines show the investors reacted to the address considering the plausible negative effects on specific businesses and companies' commitments in the businesses with China.

4. GLOBAL MACHINERY INDUSTRY

In this section, we analyze the world top 100 machinery companies. The countries are Japan, US and Germany. The data we used are stock price data of top machinery companies of which 13 companies are picked up from Germany, 43 from Japan and 44 from US. The data's time coverage is from April 24, 2019 to June 6, 2019 and we used the data base ORBIS by Bureau Van Dijk. We conducted a linear interpolation for missing data. We used EURO for German companies, JPY for Japanese ones and USD for US ones to control the fluctuation of foreign exchange rates.

Our SVD analysis provided the three depressed patterns implying the nationality effects are dominantly salient. The first principal component GRP# +1 and the second one GRP# -2 are shown in Fig. 5 and 6. The X axis is an company index and the number of them is 100. Almost all company element is positive in GRP# +1. The first principal component consists of almost all positive coefficients of the companies. Then as the first step we draw the cut-off line of 4.0 to take the representative company element over 4.0. On the other hand, in GRP# -2, though some companies have positive element values, the average absolute values of the negative values is greater than that of positive ones. Therefore, we focused and used the negative side GRP# -2. We firstly set the cut-off value as -4.0 for GRP# -2. The rest of the principal components besides GRP#1 and GRP# -2 is not picked up here for our argument due to their paucity of explanatory contribution.

Setting the cut-off line of +4.0 of GRP# +1, we find the number of representative companies of this group is 30 which consists of 28 US ones and 2 Germany (DE) ones. Among 44 US companies, 28 US companies have large element values over +4.0. The number of German ones is 2 by 13. On the other hand, there is no representative ones in Japan. In Fig. 7, the index of total raw stock prices of the selected 28 US companies is shown in which we set the initial value to be 1.0. We can say that GRP# +1 shows the US companies' pattern. In Fig. 7, the German 2 representatives' total is also presented.

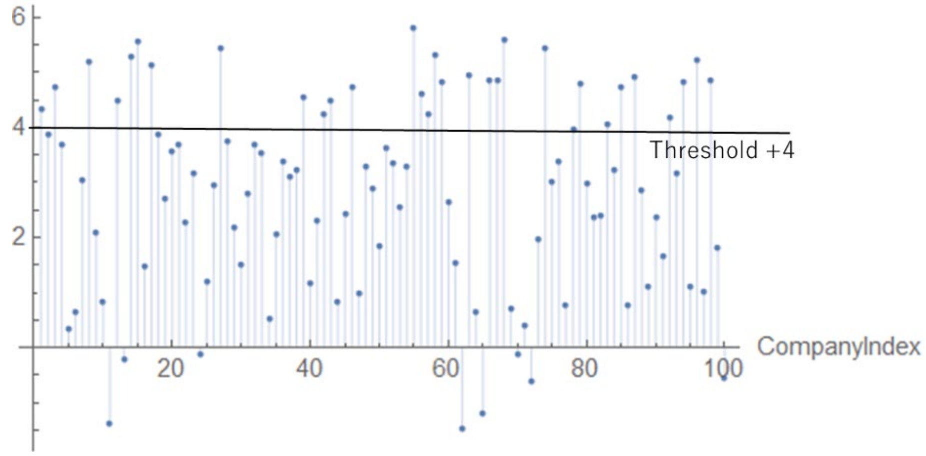

Fig. 5. GRP#1 of the top 100 machinery companies

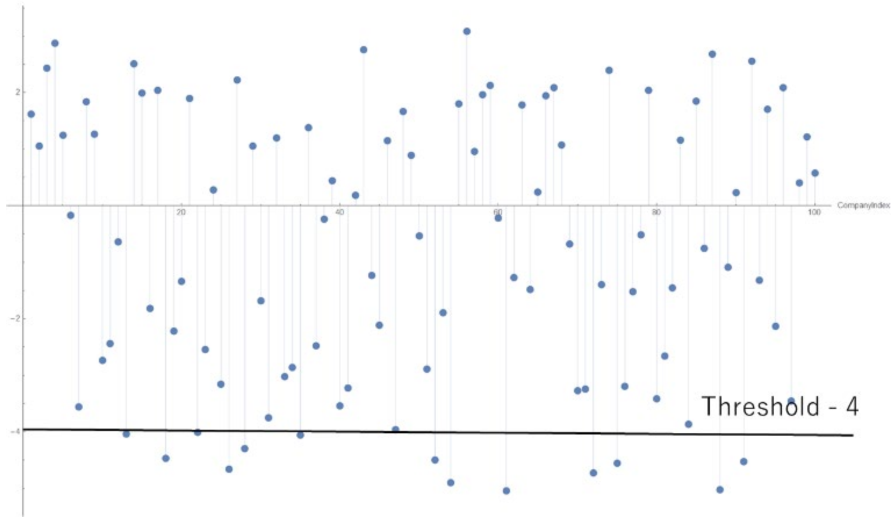

Fig. 6. GRP# -2 of the top 100 machinery companies

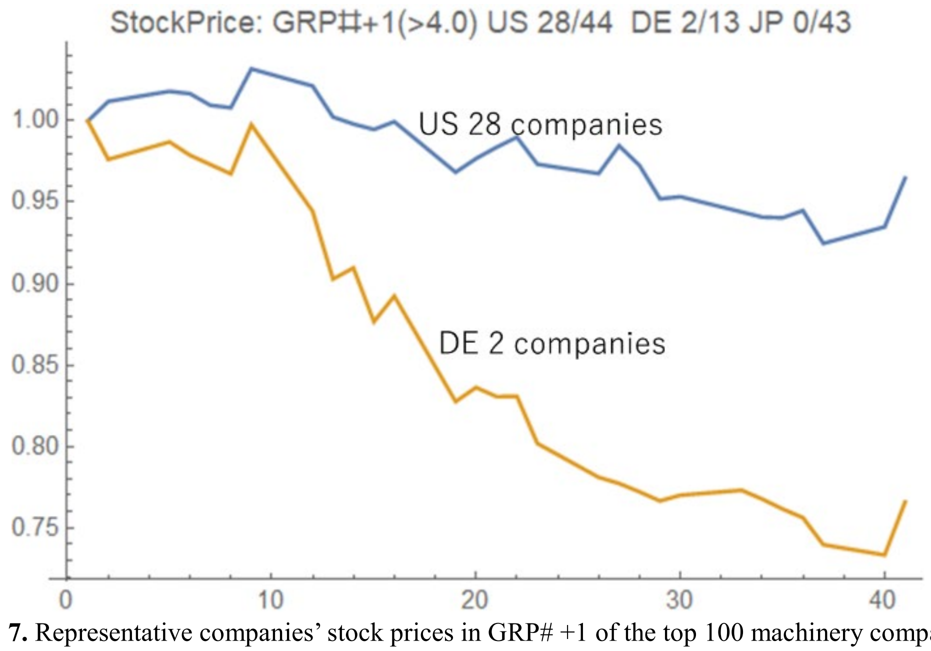

Fig. 7. Representative companies' stock prices in GRP# +1 of the top 100 machinery companies

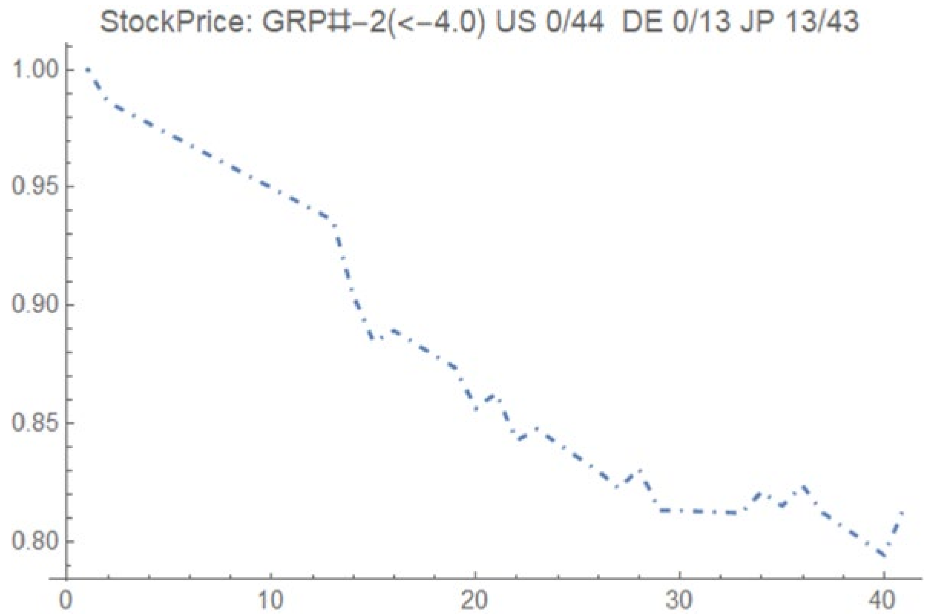

Fig. 8. The average stock price index of the representative companies of GRP#- -2

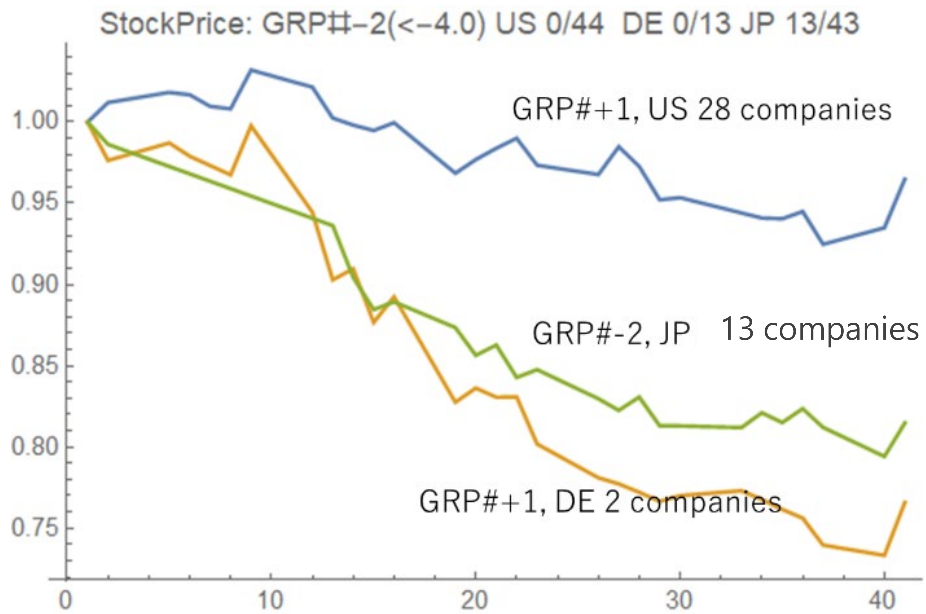

Fig. 9. Comparison of the GRP# +1 and GRP# -2 representatives' stock price movements

For GRP# -2, we obtained the number of representative companies is 13 and they are all Japanese companies. The average stock price index of the representative Japanese companies of 13 is shown in Fig. 8. Fig. 9 exhibits the average stock price indexes for GRP#1 and GRP# -2. The Japanese decline is larger than that of US.

In using SVD, the setting of cut-off values is important to interpret the results. Then, we consider the effects of cut-off value setting. Table 2 shows how the representative companies change according to the level of cut-off value. In GRP# +1, as the value goes down, the composite gets mixed and large, that is, not only US but also German and Japanese companies get in as the representative. On the other hand, in GRP# -2, only Japanese companies come in newly as the representative. In essence, GRP# +1 is interpreted to represent the property of US companies strongly. The fact that other countries' companies increase makes us hypothesize that the property is shared by also other countries' companies. On the contrary, the property of GRP# -2 is considered to be shared mainly by Japanese companies. In so far as these results, the nationality and the vulnerability perceived by investors are plausible drivers of the stock price patterns due to the crisis. The vulnerability means the steepness of declining (See Fig. 9) and likely connotes many factors such as resource commitment level and possibly propensities of product/market strategy. This

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Table 2. The number of representatives of GRP# -1 and GRP# -2 with different threshold values

threshold	GPR# +1	GPR# -2
4	US:28, DE:2, JP:0	US:0, DE:0, JP:13
3	US:34, DE:5, JP:13	US:0, DE:0, JP:26
2	US:39, DE:8, JP:22	US:0, DE:1, JP:36

imposes many research agenda for us.

5. SUMMARY OF THE RESULTS

The results we obtained through two types of analyses of the effects of the trade friction on stock prices using SVD are, firstly, that the effects differ depending on historical and resource commitment levels of companies in businesses with China and also the degree of integral fusion with daily life due to the proximity to consumers such as cosmetics, diapers and retailing, secondly, that the effects differ according to nationality of companies and possibly the vulnerability perceived by investors. These results may be inferable a priori but the confirmation is important.

6. CONCLUSION

Our research aims were, firstly, to contribute to the knowledge in finance, specifically, in grouping companies for the portfolio optimization and, secondly, to bring in some relatively new methods, specifically, SVD, for the grouping. The research of grouping by SVD leaves not least of agenda for our future research, but brings about some noticeable merits to proceed with this line of research. The first merit is to enable the visualization of the analysis results for researchers or analysts. It is expected to inspire them to develop creative ideas or insights about the objects or phenomena. For example, as Fig. 3 which shows the relationships of affiliation among the companies with real names, the analysts may be able to gain insights about the properties of the groups based on the associated knowledge with those companies' names. The second merit which is also related with the first one is that the grouping stimulates further inquiring into the factors underlying the groups, that is, what factors contribute to the formation of the groups. Though this study puts main focus on grasping and extraction of the patterns of effects of the trade friction on stock prices, this type of approach suggests us the possibility to develop more effective methods with recent data science including SVD and the importance of visualization to assist the generation of creative insights and ideas for finance. Especially, we cannot emphasize the latter, that is, the visualization of the analysis results, too much. The figures and tables we used in this study are not exhaustive. We expect the knowledge or know-how of visualization can be an important part of the data science in finance.

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