Differentiation Industry Group, Stock Performance, and the COVID-19 Pandemic: An Investigation of the Stock Exchange of Thailand

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ARTICLE INFO

Article history:
Received: 06 October 2021
Revised: 30 April 2022
Accepted: 11 June 2022

Keywords:
Stock price
Stock volume
Industry group
Emerging market

ABSTRACT

This examination into Thai listed companies empirically tests linkages among differentiation industry groups and stock performance over time. Daily data of 647 listed companies in the Stock Exchange of Thailand for the period between January 4, 2016, and August 9, 2021, was used for the empirical examination. This study investigates the subject by contrasting the relationships between differentiating industry groups and stock performance prior to the COVID-19 pandemic (January 4, 2016, to January 29, 2019) with those during the epidemic (January 30, 2019, to August 9, 2021). The hypotheses were investigated using multivariate analysis of variance on the linear combinations of differentiation industry categories on price and volume. When dividing period time into before and during the COVID-19 pandemic period, the results revealed no significant differences across industry groups in the linear combinations of the influence of stock performance as measured by stock return and percent change in volume in both periods. The findings revealed that in the Thai stock market, the Efficient Market Hypothesis holds that all stocks are correctly priced according to their inherent investing features, which all market participants know equally.

1. INTRODUCTION

Stock price prediction is an important and challenging goal in financial research [1-4]. Stock market forecasting, for example, is used by investors to make money and protect their portfolios from hazards; government agencies use it to track market swings, and scholars use it as a baseline for researching financial topics, including portfolio selection and financial derivatives pricing [5]. According to the Efficient Market Hypothesis (EMH) [6], stock prices cannot be forecast, and stocks follow a random walk pattern. On the other hand, technical analysts think that current prices reflect most information about stocks and that if price trends are detected, prices can be predicted [7].

Nonetheless, the theory's assumptions cannot always be met, and even EMH's creator revises his theory to include three levels of efficiency [8]. Much behavioral economics, finance, and other fields have challenged EMH since then [9]. Time series modeling can be done in a variety of ways. Moving average, exponential smoothing, and ARIMA are examples of traditional statistical models that linearly estimate future values. Extensive research has resulted in many prediction applications utilizing Artificial Neural Networks (ANN), fuzzy logic, and other methodologies [7]. However, the benefits of using test batteries are contingent on proper data analysis and interpretation. Some concerns have been expressed about the typical methods for statistically analyzing test battery data [10]. This study aims to look at the feasibility of using multivariate analysis of variance (MANOVA) to analyze stock market indices to predict future values.

The null hypothesis of equal mean vectors across all groups is tested using one-way MANOVA. The setup is identical to that of a one-way univariate analysis of variance (ANOVA), but the correlations between the independent variables are considered, so the variables are termed multivariate [11]. MANOVA is another statistical approach that could be used to assess test batteries, according to the authors. The MANOVA is a useful tool because it incorporates all battery tests into one matrix. The difference between groups is supported if the MANOVA shows significant effects across all test modalities. Following the MANOVA, proper post-hoc analysis can be utilized to obtain particular information about the differences between groups for each of the various tests. The MANOVA approach, while not unreasonable, can provide a more accurate picture of the influence of an independent variable on the behavioral outcome across the full battery [10].

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The EMH [6], [12] is opposed to stock forecasting based on previously accessible data. According to prior research, emerging markets aren't completely efficient, as well as the possibility that future prices of stock and returns may outperform random findings in their relationship. Forecasting time series [13] and prediction of a trend [14] are two examples of earlier stock prediction work. The link between a variety of indicators, both fundamental and technological, as well as track stock price movement is determined using a trend prediction model. Many related studies consider both technical. However, there is not clearly explained that the best algorithms and feature selections exist because the number of input features is different.

Currently, there are no widely accepted representative features or top algorithms for stock prediction. This information will show various attributes and algorithm models that were previously employed. The majority of the research in the EMH literature that forecasts stock prices has been conducted in industrialized countries such as the United States, the United Kingdom, and Western Europe due to data availability. There is little research on predicting stock price relationships in emerging markets. To our knowledge, this is one of the first studies to use a group's factors analysis to look at the link between factors in the Thai stock exchange. MANOVA. The advantage of examining in the research is to help the investor who plans to invest in stock or already does it can easily read the factors of each group and create a strategy from correlation analysis for a better return.

Allow us to share some background information about Thailand and its stock exchange. Thailand, first and foremost, has a thriving economy that draws foreign investors. Since 1997, when the Asian financial crisis hit, Thailand's economy has developed dramatically. Thailand's GDP grew four percent yearly between 2000 and 2019, putting it in the upper-middle-income category [15]. Second, Thailand is also a member of the Association of Southeast Asian Nations (ASEAN). The ASEAN Economic Community (AEC), comprised of Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam, expanded its economic cooperation from the ASEAN Free Trade Area (AFTA) to the ASEAN Economic Community (AEC) in 2015. The AEC is a collection of fast-growing markets with burgeoning populations and burgeoning economies. According to [16], at times, ASEAN financial markets exhibit a greater degree of co-movement, with intra- as well as inter-regional return and volatility dependency. Furthermore, whereas emerging equities markets have had difficulty maintaining gains since the worldwide financial meltdown, the stock market in Thailand has risen dramatically to the top of Asia's performance. As a result, Thailand presents us with an intriguing and essential but quite different context for our research than past studies.

The remainder of the paper is organized as follows: We describe data and methods in Section 2, report the empirical results in Section 3, and present our conclusions in Section 4.

2. DATA AND METHODOLOGY

Independent variables identified for this study are industry groups, namely the Agro & Food Industry, Consumer Products, Financials, Industrials, Property & Construction, Resources, Services, and Technology. While dependent variables identified for this study are stock return and percent change of volume. Daily price and volume data in the Stock Exchange of Thailand (SET) were obtained from DataStream. The data set for this study includes 647 observations from January 4, 2016, to August 9, 2021, within the framework of data that can be used for analysis. The question is addressed in this study by comparing the linkages among differentiation industry groups and stock performance before the COVID-19 pandemic period (January 4, 2016, to January 29, 2019) to those during the COVID-19 pandemic period (January 30, 2019, to August 9, 2021). SPSS was used to do the data analysis. The hypotheses were tested using the MANOVA test. The inter-correlation between the dependent variables was measured.

In two important cases, MANOVA is used. The first is when a researcher wants to execute a single, overall statistical test on a set of associated dependent variables rather than doing many separate tests. The second goal is to see how independent variables affect response patterns on dependent variables. The MANOVA provides a single thorough test of mean vector equality for several groups. Nonetheless, it is unable to determine which groups' mean vectors differ from those of other groups [10]. There are four types of statistical assessment tests of significant results from data:

Pillai’s trace (V) is a statistic with a positive value. The statistic's increasing values suggest that the impacts add more to the model. Pillai’s trace has the following formula:

$$V = trace(H\left(H+E\right)^{-1}) = \sum_{i=1}^{s}\frac{\lambda_i}{1+\lambda_i} \tag{1}$$

where, H is the hypothesis sum of squares and cross products matrix; E is the error sum of squares and cross products matrix; λ is the eigenvalue for each classifier variable.

Wilks’ Lambda (Λ) is a positive-valued statistic with a range of 0 to 1. The declining values of the statistic show that the impacts are becoming increasingly important to the model.

$$\Lambda = \frac{|E|}{|H+E|} = \prod_{i=1}^{s} \frac{1}{1+\lambda_i} \tag{2}$$

Hotelling's Trace (T^2) is the sum of the eigenvalues of the test matrix. It's a positive-valued statistic, with larger values indicating greater model impact. When the test matrix's eigenvalues are small, the value of Hotelling's trace is always bigger than the value of Pillai's trace, but the two statistics are essentially similar. As a result, the influence is unlikely to have a major impact on the model.

$$T = \sum_{i=1}^{s} \lambda_i \tag{3}$$

The greatest eigenvalue of the test matrix is Roy's largest root (R). As a result, it is a positive-valued statistic, with higher values indicating greater contributions to the model.

$$R = \sum_{i=1}^{s} \frac{\lambda_{\max}}{1+\lambda_{\max}} \tag{3}$$

The value of Hotelling's trace is always greater than or equal to the value of Roy's greatest root. When these two figures are equivalent, the effect is mostly related to only one of the dependent variables. There is a strong association between the dependent variables, or the influence does not substantially impact the model.

3. RESULTS

Descriptive statistics of the variables include the stock return and percent change of volume classified by industry group and period time both before the COVID-19 pandemic period and during the COVID-19 pandemic period, presented in the following tables.

Table 1. Descriptive statistics of variables before the COVID-19 pandemic period

Industry group	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Stock return								
Mean	-0.0008	-0.0006	-0.0002	-0.0003	-0.0005	-0.0003	-0.0003	-0.0004
Minimum	-0.0149	-0.0028	-0.0027	-0.0026	-0.0129	-0.0027	-0.0037	-0.0022
Maximum	0.0009	0.0004	0.0012	0.0012	0.0008	0.0012	0.0012	0.0021
SD	0.0023	0.0007	0.0007	0.0007	0.0013	0.0008	0.0008	0.0009
Percent change of volume								
Mean	-6.8212	-7.8421	-7.0190	-8.3995	-11.1883	-0.7514	-7.5101	-1.3433
Minimum	-228.7260	-53.9498	-243.6146	-194.3183	-264.3173	-9.4386	-167.4064	-16.5283
Maximum	-0.1793	-0.4471	-0.1410	-0.1326	-0.1698	-0.0948	-0.1869	-0.1644
SD	32.2228	10.7961	32.8972	23.4060	32.2465	1.3935	23.2771	2.8620
Observations	50	33	55	79	130	44	92	34

Note: Industry group 1 = Agro & Food Industry, 2 = Consumer Products, 3 = Financials, 4 = Industrials, 5 = Property & Construction, 6 = Resources, 7 = Services, and 8 = Technology.

Table 2. Descriptive statistics of variables during the COVID-19 pandemic period

Industry group	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Stock return								
Mean	-0.0014	-0.0006	-0.0004	-0.0002	-0.0007	-0.0004	-0.0004	0.0004
Minimum	-0.0638	-0.0020	-0.0063	-0.0050	-0.0066	-0.0060	-0.0034	-0.0027
Maximum	0.0024	0.0007	0.0028	0.0015	0.0009	0.0008	0.0043	0.0047
SD	0.0091	0.0006	0.0013	0.0009	0.0009	0.0011	0.0012	0.0013
Percent change of volume								
Mean	-46.4816	-45.9211	-63.5729	-47.6542	-33.8116	-1.4044	-20.8490	-1.1266
Minimum	-1691.0798	-301.4061	-1720.9857	-708.8315	-510.8117	-14.9078	-196.4700	-11.8757
Maximum	-0.1715	-0.5410	-0.1408	-0.0203	-0.0104	-0.0105	-0.1420	-0.1281
SD	238.7754	65.0258	245.2082	130.2458	82.4671	2.9667	39.5139	2.0600
Observations	50	34	56	80	131	45	93	35

Note: Industry group 1 = Agro & Food Industry, 2 = Consumer Products, 3 = Financials, 4 = Industrials, 5 = Property & Construction, 6 = Resources, 7 = Services, and 8 = Technology.

Tables 1 and 2 report descriptive statistics for stock return and percent change of volume classified by industry group and period time both before the COVID-19 pandemic period and during the COVID-19 pandemic period, respectively. The average stock return before the COVID-19 pandemic is negative for all industry groups, while similar results were found during the COVID-19 pandemic period except for the technology sector. Furthermore, comparing both periods, we found that the average stock return has decreased during the COVID-19 pandemic compared to before the COVID-19 pandemic period in all industry sectors except for the industrials and technology sectors.

Considering the percent change of volume, we found that the average percent change of volume is negative for all industry groups in both periods. In addition, comparing both periods, we found that the average percent change of volume has decreased during the COVID-19 pandemic compared to before the COVID-19 pandemic period in all industry sectors except for the technology sector. Figures 1 and 2 present bar charts to compare the mean value of studied variables of the two time periods (before the COVID-19 pandemic period and During the COVID-19 pandemic period) classified by industry group.

Consequently, MANOVA was conducted to see if the null hypothesis was correct. The hypothesis supporting the EMH states that there is no stock performance differentiation between industry groups. Stock return and percent change of volume data were averaged and entered as the dependent variables. Eight industry groups were entered as the independent variable. Table 3 reveals summarized results of the MANOVA test for the whole period between January 4, 2016, and August 9, 2021, and measurements of effect sizes regarding the null hypothesis.

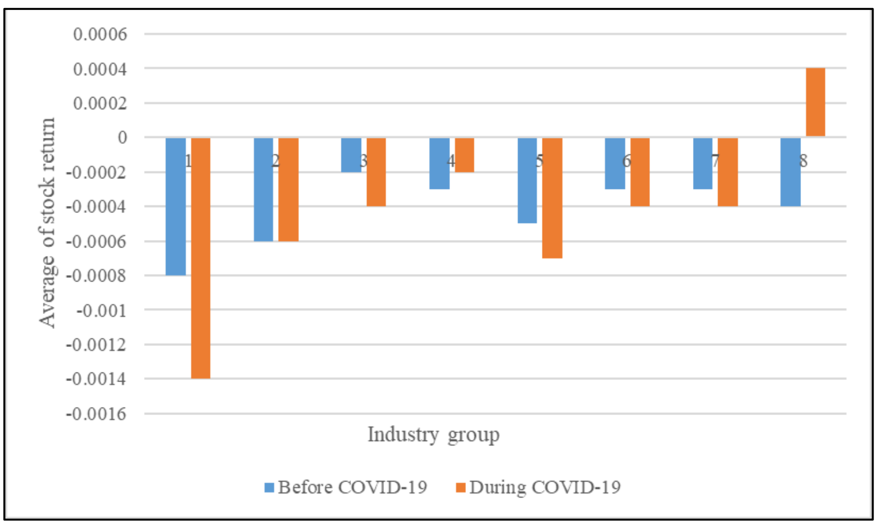

Fig. 1. Average of stock return comparison.

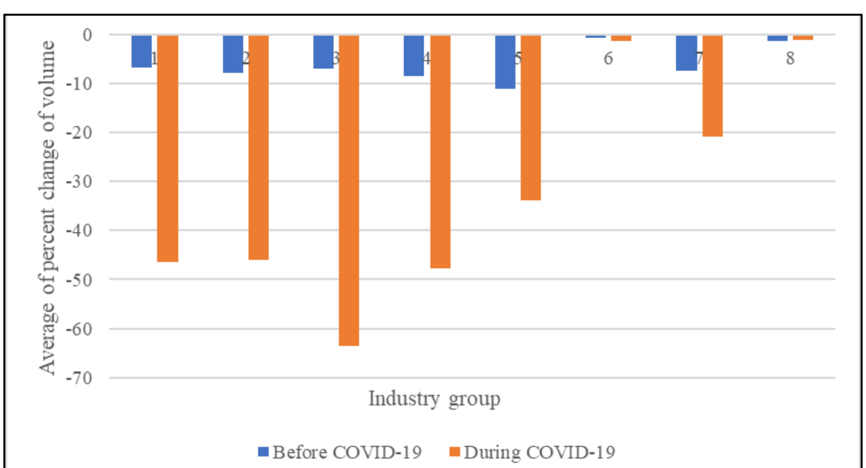

Fig. 2. Average of percent change of volume comparison.

Table 3. MANOVA test results for the whole period

Multivariate test						Box's M test				
Effect	**Value**	***F***	**df_H**	**df_E**	**Sig.**	**Box's M**	***F***	**$df1$**	**$df2$**	**Sig.**
V	.042	1.593	14	1,032	.075	1,421.520	66.590	21	282,359	.000
Λ	.958	1.591	14	1,030	.075					
T	.043	1.589	14	1,028	.076					
R	.027	1.959	7	516	.059					
Tests of between-subjects effects										
DVs		**MS_M**	**MS_R**	***F***	**Sig.**					
Return		.000	.000	1.505	.163					
Volume		6,531	3,794	1.721	.102					

Table 4. MANOVA test results for before the COVID-19 pandemic period

Multivariate test						Box's M test				
Effect	**Value**	***F***	**df_H**	**df_E**	**Sig.**	**Box's M**	***F***	**$df1$**	**$df2$**	**Sig.**
V	.034	1.290	14	1,032	.206	549.115	25.741	21	282,359	.000
Λ	.966	1.288	14	1,030	.208					
T	.035	1.286	14	1,028	.209					
R	.021	1.520	7	516	.158					
Tests of between-subjects effects										
DVs		**MS_M**	**MS_R**	***F***	**Sig.**					
Return		.000	.000	1.444	.185					
Volume		744	659	1.130	.343					

Table 5. MANOVA test results for during the COVID-19 pandemic period

Multivariate test						Box's M test				
Effect	**Value**	***F***	**df_H**	**df_E**	**Sig.**	**Box's M**	***F***	**$df1$**	**$df2$**	**Sig.**
V	.037	1.393	14	1,032	.149	1,786.879	83.764	21	282,359	.000
Λ	.963	1.392	14	1,030	.150					
T	.038	1.391	14	1,028	.150					
R	.025	1.837	7	516	.078					
Tests of between-subjects effects										
DVs		**MS_M**	**MS_R**	***F***	**Sig.**					
Return		.000	.000	1.312	.242					
Volume		25,460	16,683	1.526	.156					

The MANOVA test findings and effect size measures for the null hypothesis are given in Table 3 for the entire time. The influence of stock performance, as assessed by stock return and percent change in volume, was measured in linear combinations for industry groupings. The significance of Box's M $p(0.000) < \alpha(0.01)$ in the table indicates that the null hypothesis that the covariance matrices were identical was rejected. As a result, the dependent variables' covariance matrices were discovered to be uneven among industrial groups. The assumption of equal covariance matrices was broken by MANOVA. As a result of the significant $df2$ value (282,359) found in this research, the multivariate normal condition can be assumed to be credible.

Table 3 reveals insignificant $p(0.075) < \alpha(0.10)$ for Pillai's Trace and Wilks' Lambda, $p(0.076) < \alpha(0.10)$ for Hotelling's Trace and $p(0.059) < \alpha$ (0.10) for Roy's largest root MANOVA effect. As a result, it was proven that there was a statistically significant difference across industry groupings when it came to the linear combinations of stock performance impact at the significance level of 0.1. The table also shows the results of the univariate ANOVA test after significant MANOVA. However, following up with a univariate test, we found that there was no significant influence in terms of stock return $p(0.163) > \alpha$ (0.10) and percent change of volume $p(0.102) > \alpha$ (0.10).

Table 4. MANOVA test results for before the COVID-19 pandemic period

Table 4 summarizes the MANOVA test results and effect size measures in relation to the null hypothesis prior to the COVID-19 pandemic. The linear combinations of stock performance, as assessed by stock return and percent change in volume, were used to rank industry categories. The significance of Box's M $p(0.000) < \alpha$ (0.01) in the table suggests that the null hypothesis of equal covariance matrices has to be rejected; thus, the covariance matrices of the dependent variables were found to be uneven between industry groupings. For the purposes of MANOVA, the assumption of equal covariance matrices was broken. The multivariate normal condition is assumed to be possible. The outcome can be carried out because the *df*2 value (282,359) was seen in this analysis.

Table 4 reveals insignificant $p(0.206) > \alpha$ (0.05) for Pillai's Trace, $p(0.208) > \alpha(0.05)$ for Wilks' Lambda, $p(0.209) > \alpha(0.05)$ for Hotelling's Trace and $p(0.158) > \alpha$ (0.05) for Roy's largest root effect of MANOVA; thus, it was determined that no statistically significant difference existed between industrial groupings when it came to the linear combinations of stock performance impact. The table also shows the results of the univariate ANOVA test after significant MANOVA. Following up with a univariate test, we found that there was no significant effect in terms of stock return $p(0.185) > \alpha(0.05)$ and percent change of volume $p(0.343) > \alpha$ (0.05). Therefore, it was confirmed that there was no difference in industry groups on stock performance in respect of stock return and percent change of volume before the COVID-19 pandemic period.

Table 5. MANOVA test results for during the COVID-19 pandemic period

Table 5 summarizes the MANOVA test results and effect size measures in relation to the null hypothesis during the COVID-19 pandemic. Stock performance, as measured by stock return and percent change in volume, was used to rank industry groups. The significance of Box's M $p(0.000) < \alpha$ (0.01) in the table suggests that the null hypothesis of equal covariance matrices has to be rejected; thus, the dependent variables' covariance matrices across various industrial sectors were found to be unequal. For the purposes of MANOVA, the assumption of equal covariance matrices was broken. As a result of the significant *df*2 value (282,359) found in this research, the multivariate normal condition can be assumed to be credible.

Table 5 reveals insignificant $p(0.149) > \alpha(0.05)$ for Pillai's Trace, $p(0.150) > \alpha(0.05)$ for Wilks' Lambda and Hotelling's Trace and $p(0.078) < \alpha(0.10)$ for Roy's largest root effect of MANOVA. Therefore, when it comes to the linear combinations of stock performance influence, it was proved by most of the test statistics that there was no statistically significant variation between industry groupings. The table also shows the results of the univariate ANOVA test after significant MANOVA. Following up with a univariate test, we found that there was no significant influence in terms of stock return $p(0.242) > \alpha(0.05)$ and percent change of volume $p(0.156) > \alpha$ (0.05). Therefore, it was confirmed that there was no difference in industry groups on stock performance regarding stock return and percent change of volume during the COVID-19 pandemic.

According to the MANOVA results, we found significant differences in stock return and percent change in volume across industry sectors for the whole period. However, there are no significant differences in perceptions of the impact of linear combinations of industrial groupings on Thai stock performance, measured by stock return and percent change in volume when dividing period time into before the COVID-19 pandemic period and during the COVID-19 pandemic period. Therefore, the hypotheses were not proven. Furthermore, the insignificant MANOVA results are confirmed by follow-up ANOVA results. In terms of stock return and percent change in volume, nonsignificant follow-up ANOVA findings were reported. According to the findings, we might conclude that when dividing the study period by the COVID-19 pandemic period, the EMH is confirmed. This study implies that, in the Thai stock market, all stocks are precisely priced based on their inherent investing features, which all market participants have equal awareness of.

4. CONCLUSION

MANOVA is commonly used to find the relation between multiple dependent and independent variables. In this study, MANOVA is employed to generate the model from the relation of financial factors. Stock return and percent change of volume data were averaged and entered as the dependent variables. Eight industry groups were entered as the independent variable. The data set for this study includes 647 observations between January 4, 2016, and August 9, 2021. This study addresses the question by examining the linkages among differentiation industry groups and stock performance before the COVID-19 pandemic period (January 4, 2016, to January 29, 2019) to those during the COVID-19 pandemic period (January 30, 2019, to August

9, 2021). When the study period is divided into before and during the COVID-19 pandemic period, the MANOVA results revealed no statistically significant difference across industry groups when it came to the linear combinations of stock performance impact. The results showed that the EMH maintains in the Thai stock market that all stocks are perfectly priced according to their inherent investment properties, the knowledge which all market participants possess equally.

These discoveries have many ramifications. Investors can choose their assets based on the projected returns that have been examined. Furthermore, investors can build a strong portfolio by investing in lucrative firms. This research may aid researchers, businesses, investors, and governments make informed stock market decisions. Researchers can also use other models to examine time series prediction. It is possible to construct an optimal portfolio for individual investors, and regulators can make important decisions to ensure the smooth operation of the stock market. The financial information aspects of each organization differ depending on their sectors.

Nonetheless, there are some flaws in this research. The SET includes several sectoral indices that may have provided a more comprehensive analysis and led to greater investment returns for investors. Furthermore, the research may have focused on comparing the accuracy of estimating returns over different time horizons. Future research could look at stock price forecasting and comparisons in developed and emerging stock markets. Furthermore, using breakthrough technology to foresee the long future will ensure good returns. The focus will be on comparing various sectorial indexes from Thailand and other nations in order to gain more insight into their portfolio structure, risk and return, performance, and trading efficiency.

Additionally, as the data currently used in the analysis is cross-sectional, we cannot add the "Period time" variable as a factor independent variable in this analysis. Suppose the "Period time" variable (Before the COVID-19 pandemic period and During the COVID-19 pandemic period) is taken as a factor. The interaction between industry groups and period time factors with factorial experiments can be performed in a statistical test. This will result in more evident research results and a more comprehensive discussion. Furthermore, future research may consider using factorial MANOVA to determine whether or not industry sector and period time and their interaction significantly affect optimally weighted linear combinations of the stock return and percent change of volume.

ACKNOWLEDGMENT

Financial support from the Faculty of Business Administration and Accountancy, Khon Kaen University, under grant number 013/2564, is gratefully acknowledged. An earlier version benefitted from valuable comments from participants of the SIBR Conference on Interdisciplinary Business and Economics Research, Osaka, Japan.

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