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TIME-SERIES ANALYSIS OF DYNAMIC LINKAGES AMONG TOPIX-17 SECTOR INDICES AND DEVELOPMENT OF INVESTMENT PORTFOLIO STRATEGIES UNDER UNCERTAINTY

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Abstract: *In this study, first, we examine how dynamic linkages among TOPIX-17 sector indices and economic indicators affect one another. We usea vector error correction model and a generalized autoregressive conditional heteroscedasticity model to represent the dynamic relationships among worldwide market indicators, including stock indices, energy prices, and commodity prices. Second,we conduct time-series analysis to predict future prices of TOPIX-17 at five years. Third, we addressthe question of how one should invest in the Japanese market. We conduct simulations of the market behaviorwith stochastic disturbance to develop an optimal multistep investment strategy based on an expectedvaluemaximizationmodel and a regret minimization model.The results provide a new perspectiveondecision-making in investment portfolio management by governments, companies, and investors.*

Keywords: *TOPIX-17, Dynamic Linkage, Time-SeriesAnalysis, Business Forecasting, Investment Strategy*

1. INTRODUCTION

Policy-makers and investors have to make optimal decisions under uncertainty. Sources of uncertainty such as price volatilityin the energy and stock markets make such decision-making difficult. The Japanese economyhas been unstablesince the collapse of the bubble economy in 1990, and this instability is reflected in the volatility of the Tokyo Stock Price Index (TOPIX). This index is based on all the domestic common stocks listed on the First Section of the Tokyo Stock Exchange (TSE). TOPIX is a measure of the overall trend in stock market prices, and it serves as a benchmark for investment in Japanese stocks.The TOPIX-17 Series comprises sector indices for 17 categories (Table 1).

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The Japanese economy has been strongly affected by price instability in various financial markets around the world, including stock, currency, oil, and gold markets. For instance, the price of West Texas Intermediate (WTI) crude was US$12/bbl in 1999 but it increased 11-fold over the next 10 years, owing to the price increases and volatility brought by the2003 invasion of Iraqand the 2008 global financial crisis, among other events.

Turning to stock index prices, the Dow Jones Industrial Average (Dow) of the New York Stock Exchange reached a peak in 2007 but dropped by 50% within a year because of the global financial crisis.Since the crisis, US stock priceshave continued to show tremendous volatility due to various sources of financial instability,such as the Eurozone debt crisis.

Therefore, an important challenge is to analyze how linkages among market prices affect the development of investment strategy. In this paper, we analyze the dynamic linkage among world markets and develop a prediction model that employstime-series analysis. Finally, we develop an optimal investment strategy based on decision-makingto maximizeexpected value and minimizeregretvalue.

2. RESEARCH OBJECTIVES

2.1. Previous Research

Some papershave looked at the dynamic linkages among Japanese markets. For example, Jasic and Wood (2004) examined trading signals generated from out-of-sample short-term predictions of daily stock market returnsfor the Standard & Poor's 500, DAX, TOPIX,and Financial Times Stock Exchange (FTSE) indices from 1965 to 1999 and analyzed the profitability of those signals. Chang *et al.* (1999) examines the behavior of index return and volatility of TOPIX. Hung *et al.* (2009) analyzed the weakform of theefficient market hypothesis for the large- and small-capitalization TOPIX and FTSE indices by using parametric and nonparametric variance ratio tests.

However, few studies have comprehensively dealt with the linkagesamong TOPIX-17 sector indices, economic indicators, other stock indices, energy prices, and commodity prices. In addition, few have devised investment portfolio strategies based on the results of price predictions.

2.2. Research Objectives

In order to provide a new perspective for decision-makers worldwide, this research has three objectives: (1) to analyze the dynamic linkagesamongvarious indicators by time-series analysis, (2) to predict the future TOPIX price at five years on the basis of theanalysis of the dynamic linkages, and (3) to find an optimal investment strategy by using the predictionresults.

3. DATA SOURCES

3.1. Dataset

The sample periodincludes 22 years, from August 1993 to July 2014,including the global financial crisis. In this study, we analyzed all 17 of the TOPIX-17 sector indices toassess how they affected one another. Also, we selected 13 indicators that affect the TOPIX-17 from among stock indices, economic indicators, energy prices, and gold prices (listed in Table 1).

Table 1
Indicator Variables

Stock Indices	Economic Indicators	Energy Prices	Gold Prices
Dow (US)	Money base	Natural gas	Gold
FTSE (UK)	Unemployment rate	Corn	
Hang Seng (Hong Kong)		Uranium	
Nikkei (Japan)		WTI	
STI (Singapore)			
DAX (Germany)			

TOPIX-17		
Foods	Energy resources	Construction & materials
Raw materials & Chemicals	Pharmaceutical	Automobiles & Transportation equipment
Steel & Nonferrous metals	Machinery	Electric appliances & Precision instruments
IT & Services, Others	Electric power & Gas	Transportation & Logistics
Commercial & Wholesale trade	Retail trade	Banks
Financials	Real estate	

STI: Straight Times Index; DAX: Deutscher Aktienindex.

3.2. Data Properties

We applied the augmented Dickey–Fuller test to test for a unit root. The results are shown in Table 2, and all indicators are found to have a unit root at the 1% level of significance. In addition,we checked for the existence of cointegrationby the Johansen cointegration test.We thenapplied the vector error correction model (VECM) to identify the cointegrating relationships present in the data series.As shown in Table 3, we found the existence of at most 28 cointegrating relationships. Therefore, we used the VECM to check the Granger causality.

Table 2
Augmented Dickey–Fuller Test Results

	t-statistic	Prob.		t-statistic	Prob.
Corn*	-2.307	0.428	IT & Services, Others*	-2.050	0.570
Dow*	-2.195	0.490	Real estate*	-1.859	0.673
DAX*	-2.094	0.546	Electric appliances & Precision instruments*	-1.604	0.789
FTSE*	-2.144	0.518	Transportation & Logistics*	-1.739	0.731
Hang seng*	-3.272	0.073	Commercial & Wholesale trade*	-3.006	0.133
Money base*	-2.047	0.572	Retail trade*	-2.044	0.574
Natural gas*	-3.136	0.100	Banks*	-1.684	0.756
Nikkei*	-1.703	0.747	Financials*	-2.244	0.463
STI*	-2.310	0.426	Foods*	-1.840	0.682
Unemployment rate*	-1.834	0.685	Energy resources*	-2.089	0.549
Uranium*	-1.196	0.909	Construction & Materials*	-1.422	0.853
WTI*	-3.455	0.047	Raw materials & Chemicals*	-2.502	0.327
Gold*	-1.888	0.658	Pharmaceutical*	-1.785	0.709
			Automobiles & Transportation equipment*	-2.514	0.321
			Steel & Nonferrous metals*	-2.036	0.579
			Machinery*	-2.268	0.450
			Electric power & Gas*	-2.288	0.439

*: Significant at the 5% level.

Table 3
Johansen Cointegration Test

No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Prob.**
None	0.800	4209.559	NA	NA
At most 1	0.789	3810.643	NA	NA
At most 2	0.756	3425.244	NA	NA
At most 3	0.705	3075.521	NA	NA
At most 4	0.681	2773.160	NA	NA
At most 5	0.651	2489.554	NA	NA
At most 6	0.616	2228.448	NA	NA
At most 7	0.558	1991.251	NA	NA
At most 8	0.528	1788.731	NA	NA
At most 9	0.489	1602.703	NA	NA
At most 10	0.469	1436.098	NA	NA
At most 11	0.457	1279.119	NA	NA
At most 12	0.419	1127.603	NA	NA
At most 13	0.397	992.920	NA	NA
At most 14	0.369	867.487	NA	NA
At most 15	0.325	753.116	NA	NA
At most 16	0.310	655.732	NA	NA
At most 17	0.296	563.794	NA	NA
At most 18 *	0.263	476.719	334.984	0.000
At most 19 *	0.235	401.118	285.143	0.000
At most 20 *	0.213	334.571	239.235	0.000
At most 21 *	0.199	275.055	197.371	0.000
At most 22 *	0.184	220.060	159.530	0.000
At most 23 *	0.164	169.591	125.615	0.000
At most 24 *	0.145	125.138	95.754	0.000
At most 25 *	0.116	86.348	69.819	0.001
At most 26 *	0.097	55.660	47.856	0.008
At most 27 *	0.069	30.447	29.797	0.042
At most 28	0.050	12.698	15.495	0.126
At most 29	0.000	0.006	3.841	0.938

CE: Cointegrating equations; *: Significant at the 5% level.

4. VERIFICATION OF DYNAMIC LINKAGES

4.1. Methodology

Granger causality is used to test for dynamic linkages; when a linkage is found, a vector autoregressive model or VECM is typically applied. A suitable model is then determined according to the characteristics of the data. In this study, since co-integration among data series were found, a VECM was adopted. Kitaoka (2008) showed that the basic equationsdescribing the VECM are given below:

$$\Delta Y_t = \sum_{i=1}^{N-1} B_i \Delta Y_{t-i} - \Pi Y_{t-1} + U_t \tag{1}$$

$$B_i = \sum_{j=i+1}^{n} A_j \,, \quad \Pi = I - \sum_{j=1}^{n} A_j \,, \quad \Delta Y_{t-1} = Y_{t-1} - Y_{t-i-1} \tag{2}$$

(Yt: Variables, A_i *and* B_i: parameter (Lag i), Ut: disturbance term, Π: determinant)

The number of cointegrating relationships equals the rank of the matrix. The Johansen co-integration test indicated the existence of at most 28 co-integrating relationships. Also, we found the Granger causality among the variables.

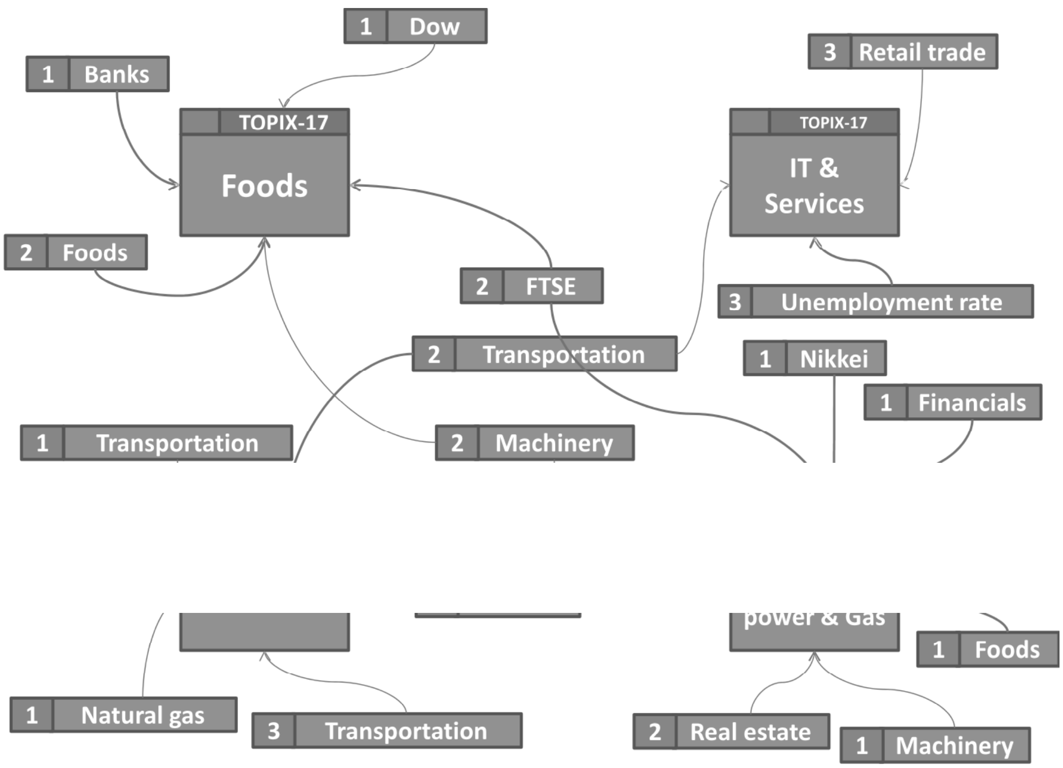
4.2. Resultsof Dynamic Linkage Analysis

What indicators have had a strong impact to the TOPIX-17 sector indices, and how strong of an impact was it? Figure 1 shows the dynamic linkages in 4 of 17 sectors in the TOPIX-17 Series as an example. Here we can see that theFoodsector has been strongly influenced byDow and FTSE (Lag 2) and theBank, Foods (Lag 2), and Machinery (Lag 2) sectors. Various other dynamic linkages are seen for the other three sectors as well. In addition, we foundthat overall TOPIX indiceswere especially strongly affected by FTSE andDow, and the Foods, Machinery and Transportation & Logistics sectors.

4.3. Prediction Methodology

In aVECM, the variance calculated from historical data is applied to the theoretical data. Typically, volatility is low when the economy isgrowing steadily and high when the economy is shrinking. This means that there is heteroscedasticity in the data, which canbe handled by using a generalized autoregressive conditional heteroscedasticity (GARCH) model. GARCH models use regression to estimate the variance h_t in term t from the historical variance h_{t-1}. Compared with a VECM, a GARCH model provides more detailed variance; therefore, GARCH models are more likely to yield an accurate prediction. We used both a VECM and a GARCH model to predict future prices for the period from August 2014 to August 2019.

Figure 1: Dynamic Linkages of TOPIX-17 Sector Indices (Foods, IT& Services, Real estate, and Electric power & Gas) in the VECM



The GARCH model is described by the following equations:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + U_t \tag{3}$$

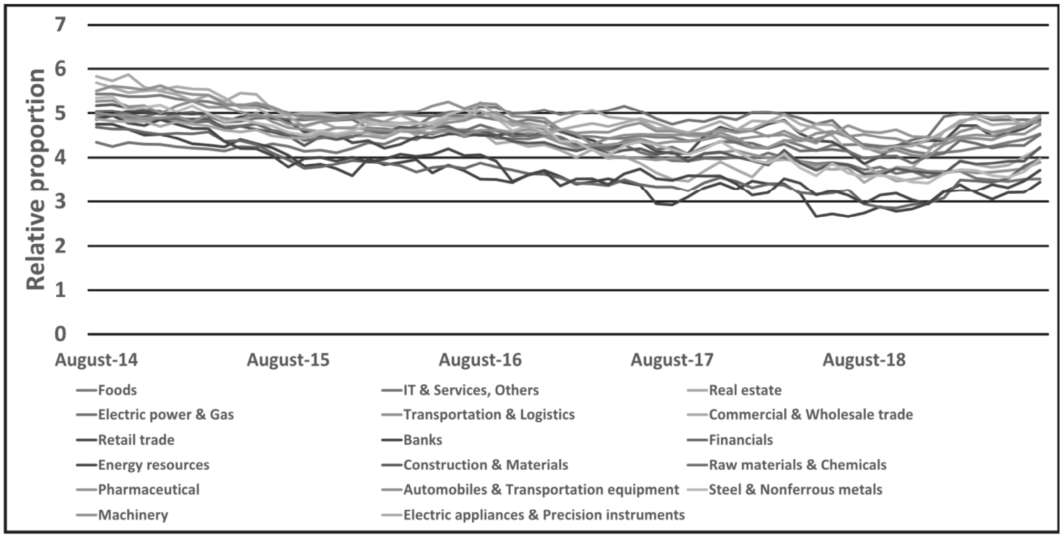
$$U_t = Z_t\sqrt{h_t},\quad h_t = \alpha_0 + \alpha_1 U_{t-1}^2 + \gamma_1 h_{t-1} \tag{4}$$

αi, βi, γi: parameters (term i), $Zt \sim N(0, 1)$

4.4. VECM Prediction Results

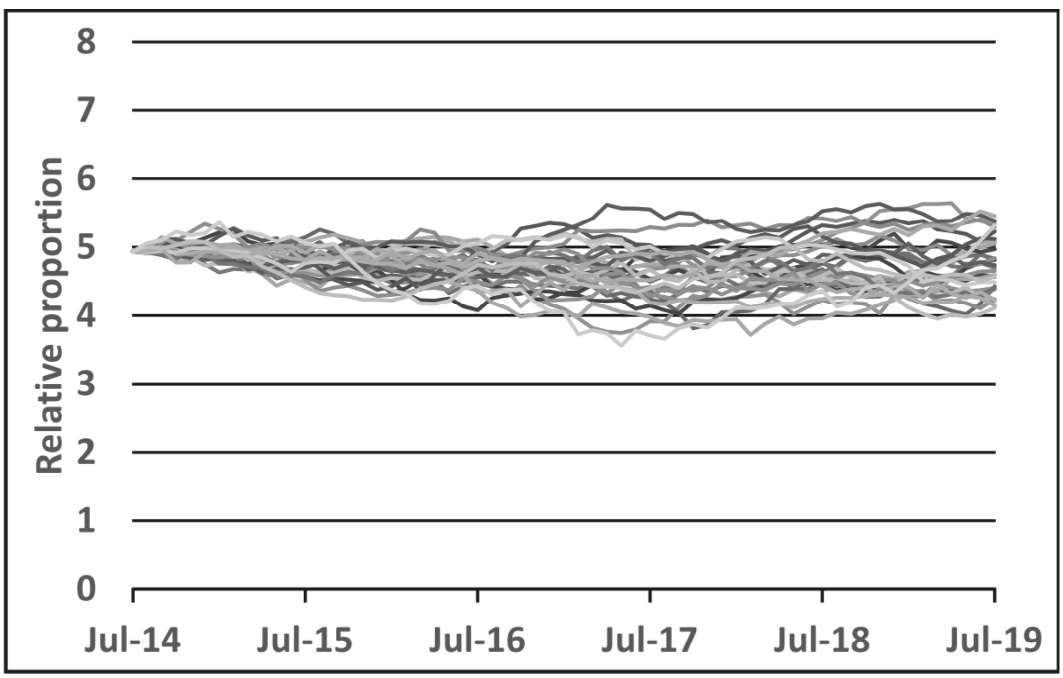
The predicted averagesfrom VECMare shown in Figure 2. The relative proportions in Figure 2 are the changes relative to December 2002. The overall trend was downward, decreasing byabout 14.5% over five years. The sectors predicted todecrease by more than 15% over the five years wereSteel & Nonferrous metals, Banks, and Real estate. In contrast, theElectric appliances & Precision instruments sector is expected to increase by 1.62% over its current value.

Figure 2: Prediction of TOPIX-17 Prices by VECM



The VECM prediction resultsfor the Transportation & Logistics sector are shown in Figure 3 as an example.

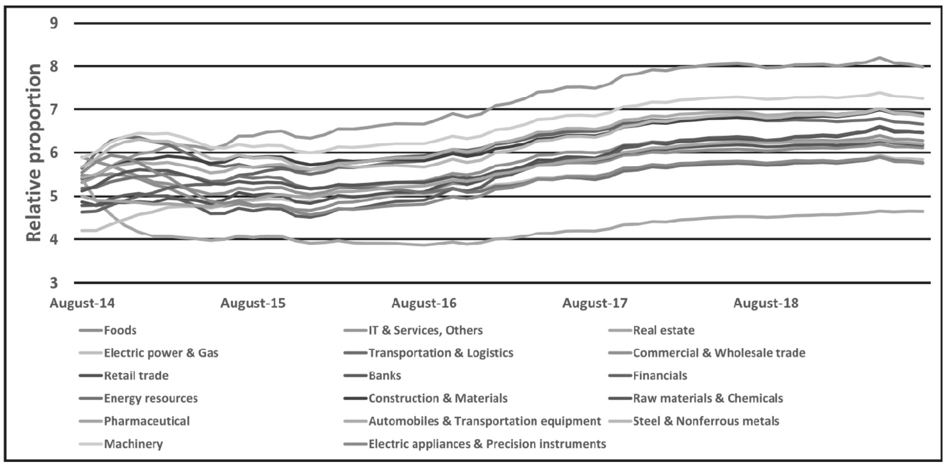
Figure 3: VECM Prediction Results for the Transportation & Logistics Sector (Individual Runs Shown)



4.5. GARCH Prediction Results

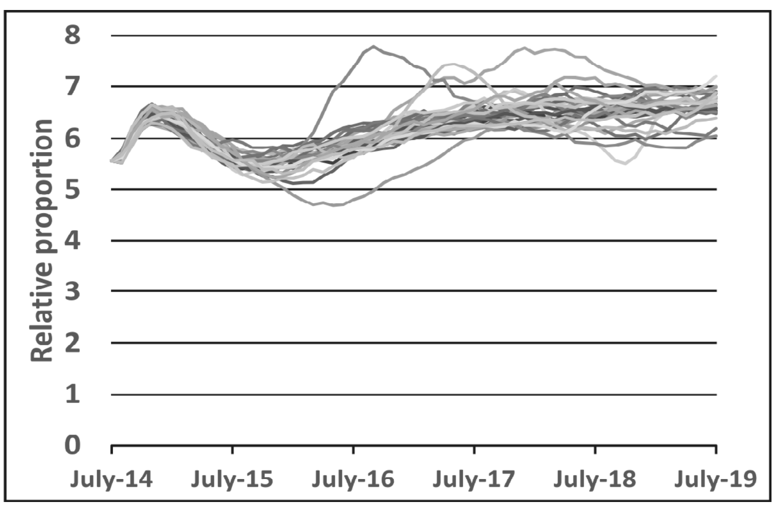
The predictionresults from the GARCH model are shown in Figure 4.It can be clearly seen that the overall trend was predicted to rise slightly. Over five years, theIT&services and financialsectors showed a steady increase, bynearly 50%, in stark contrast to the realestate sector. The volatility from the GARCH model is smaller than that from the VECM, and the trend is different. However, both models predicted a notable drop in the real estate sector.

Figure 4: Prediction of TOPIX-17 by GARCH



The GARCH prediction resultsforthe Transportation & Logistics sector are shown in Figure 5 as an example.

Figure 5: GARCH Prediction Results for the Transportation & LogisticsSector (Individual Runs Shown)



5. DEVELOPMENT OF OPTIMAL INVESTMENT STRATEGY

In this study, we developedan optimal portfolio strategybased on theVECM and GARCH predictions. Part of the optimization strategy was to maximizeexpected value, which is often used for decision-makingunder uncertainty. We also employed a generalized distance-based regret minimizationmodel to deal with the higher uncertainty that comes with irreversible decision-making.

The regret minimizationmodel providesa way to develop a mixed strategy where the maximum regretvalue—here, the gap between the most profitable strategy and another strategy—is minimized. However, if the simulations are a non-stationary process, the potential future pricesdiverge due to the variance in each period. In that case, we cannot say whether an investment strategy decided at the beginning is optimal and would need to decide a new strategyfor every term *t*. Thus, we expanded the strategy to include the multistepdecision-makingmodel developed by Mori *et al.* (2012), and we find a suitable solution by updatingthe strategy periodically.

5.1. Expected ValueMaximization Model

To determine the maximum expected value, we started with the price series simulation PrcSims (*M*, *t*, *N*) and the purchase volume estimate ALF (*N*, *t*), where *M* is the number of simulations, *t* is the term, and *N* is the commodity. When the initial budget equals 1, we have the following constraint:

$$\sum ALF(N,\ \text{"1"}) \times PrcSims(M, \text{"1"},\ N) \leq 1.0 \tag{5}$$

If the estimates are perfect predictions, we can use the information tocreate the portfolio ALF*(*M*, *N*, *t*). Portfolio price X(*M*,*t*) is given by

$$X(M,\ t) = \sum ALF^*(M,\ N,\ t) \times PrcSims(M,\ t,\ N) \tag{6}$$

When ALF*(*M*, *N*, *t*+1) is repurchased in the portfolio ALF*(*M*, *N*, *t*) by using PrcSims(*M*, *t+1*, *N*), we have the following constraint:

$$\sum ALF^*(M,\ N,\ t+1) \times PrcSims(N,\ M,\ t+1) \leq \sum ALF^*(M,\ N,\ t) \times PrcSims(N,\ M,\ t) \tag{7}$$

Thus, with the discount rate denoted as*d*, the expected value maximizationmodel is as follows.

$$max.\ \sum_t (1-d)^t \sum_M X(M,\ t)/M \tag{8}$$

5.2. Regret Minimization Model

If future priceswere known, the best strategy would be to invest in only theone investment expected to increase the most. The following equation gives the difference between portfolio price X(*M*, *t*) and the price in the case where only the one best investment is made:

$$\sum_{N} PrcSims(M,\ t,\ N) \times ALF^{*}(M,\ N,\ t) - X(M,\ t) = A\_UP(M,\ N,\ t) - A\_LO(M,\ N,\ t) \tag{9}$$

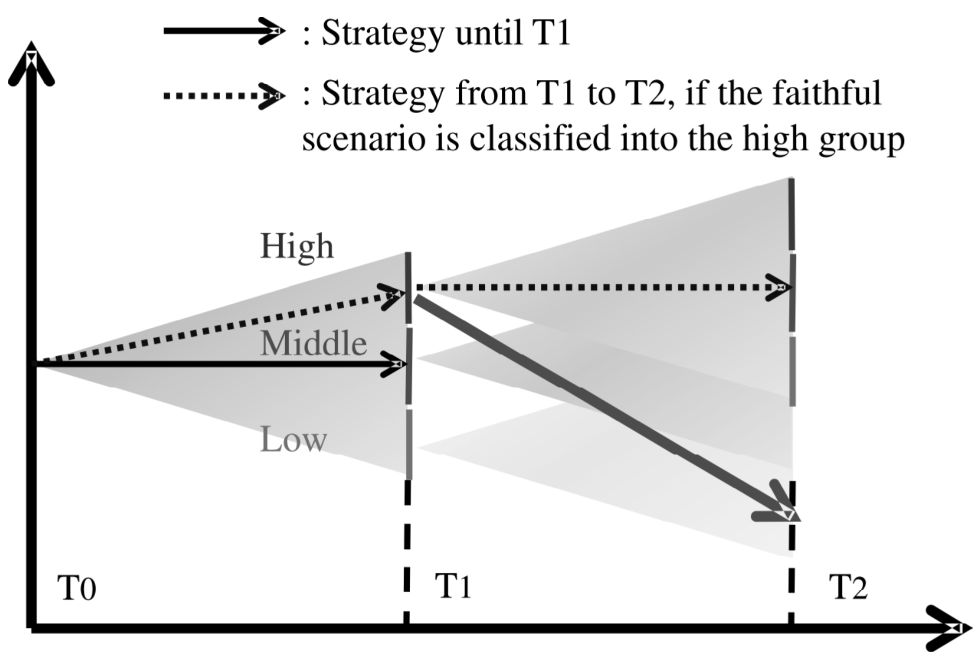
A_UP(*M*, *N*, *t*) and A_LO(*M*, *N*, *t*) represent the regret-value and the benefit, respectively. We minimize the Minkowski generalized distance for regret by using the following equation (Mori *et al.*, 2012).

$$D = \left\{\sum_{t} (1-d)^{t} \sum_{M} \sum_{N} A\_UP(M,\ N,\ t)^{\theta}\right\}^{\left(\frac{1}{\theta}\right)} \tag{10}$$

5.3. Multistep Decision-making Model

The concept of the multistep decision-making model is illustrated inFigure 6. In this model, exactly one optimized strategy is selected in term T_0 and the othersimulationsrepresent the future uncertainties at period T_1. When in term T_1, a new decision strategy is generated on the basis of the revised information in. By classifying the simulation runs into high, middle, and low groups, we can at least ascertain which group the faithful scenario belongs to, even if future uncertainty is not completely resolved. This method enables the strategy to be improved by recalculating the next term strategy using simulation runs that have the same moving character. This yields what we will call a pseudo-faithful scenario.

Figure 6: Multistep Decision-making Model



However, in this study, random noise is added to the pseudo-faithful scenario, and so we need to considerthecase where the pricedrops dramatically (e.g., from the high to low group). In this case, the expectedvalue maximization model focuses on only the average of the scenarios through the high group, and the results might be suboptimal. The regret minimization model, however, can resolve this problem because this method minimizes the Minkowski distance between the expected and maximalregretvalue. Thus, we consider various cases by applying both models to multistep strategies.

5.4. Results from the Multistep Decision-making Model

The initial asset valuewas assumed to be 1. We conducted 10 simulation runs with an estimation period of five years in themultistep strategy; the investment strategy is updated every 20 months, resulting inthree investment strategy periods.

5.4.1. Results from theMultistep Decision-making Model Maximizing Expected Value (VECM)

The accumulated value of the TOPIX-17 indices is shown inFigure 7. The accumulated value is dispersed among the sectors.Under expected value maximization model, the portfolio price increased by a maximum of 139.1%, a minimum of 115.1%, and an average of 126.2% over five years.

Figure 7: Accumulated Value of TOPIX-17 Indices under the Expected Value MaximizationModel (VECM)

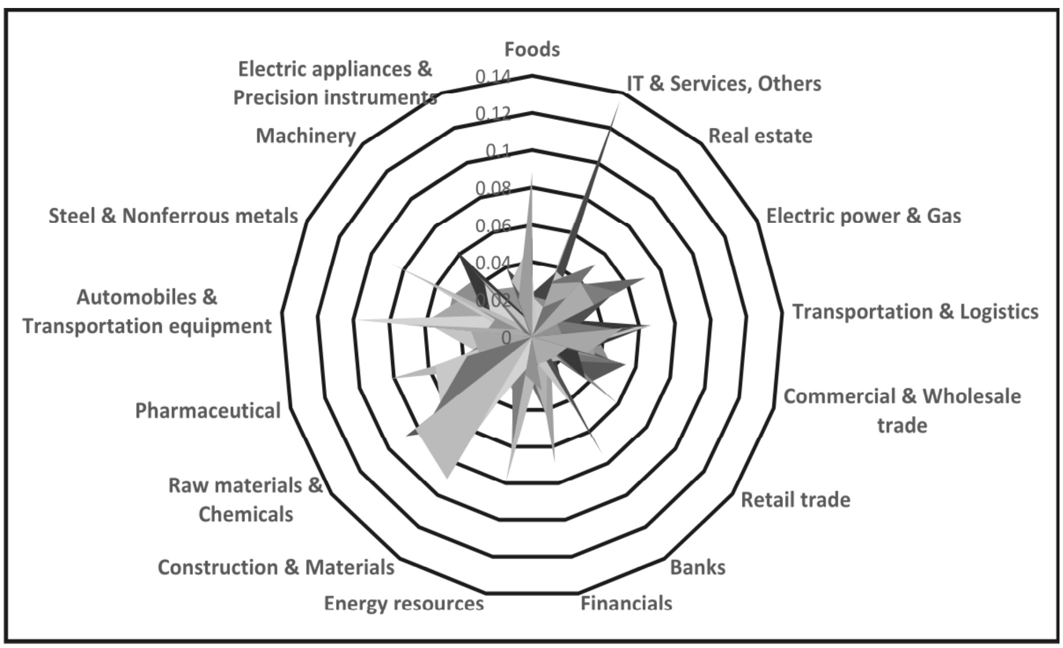
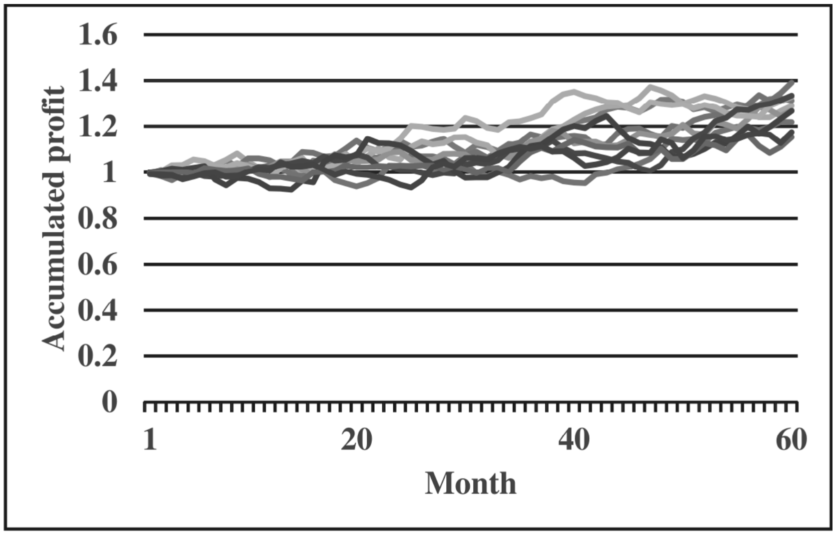


Figure 8: Accumulated Gains from TOPIX-17Sectorsunder the Expected Value Maximization Model (VECM)



5.4.2. *Results from the Multistep Decision-making Model Minimizing Regret (VECM)*

The accumulated value of TOPIX-17 indices is shown in Figure 9. The accumulated value is concentrated in the Foods, Steel & Nonferrous metals, and Electric power & Gassectors. Under the regret minimization model, the portfolio price increased by a maximum of 117.1%, a minimum of 101.7%, and an average of 108.6%over five years.

Figure 9: Accumulated Value of TOPIX-17Indicesunder the Regret Minimization Model (VECM)

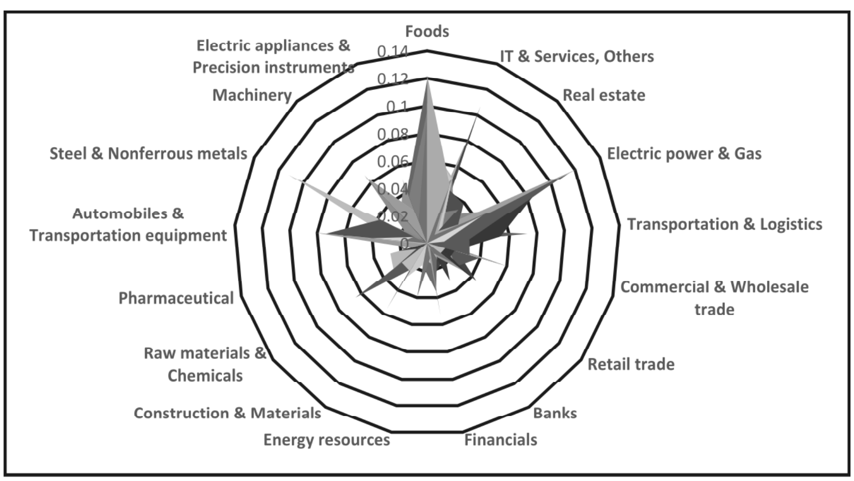
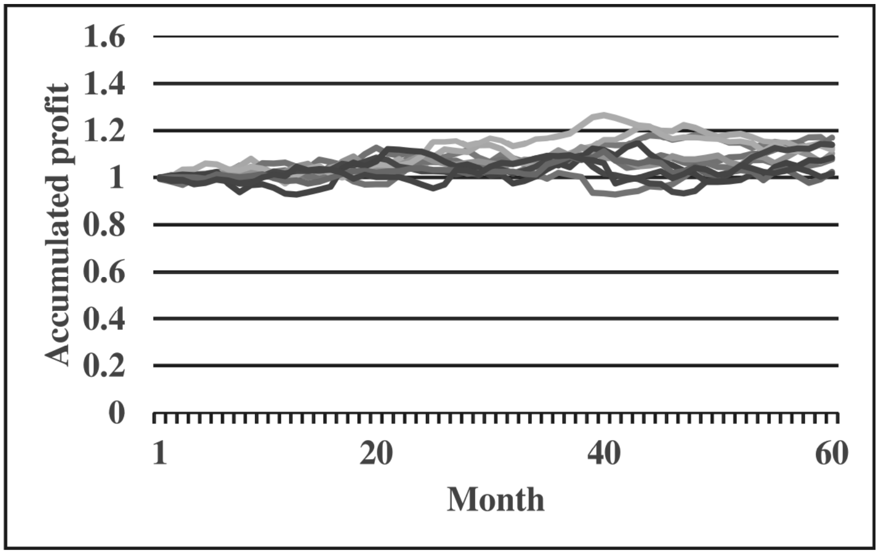


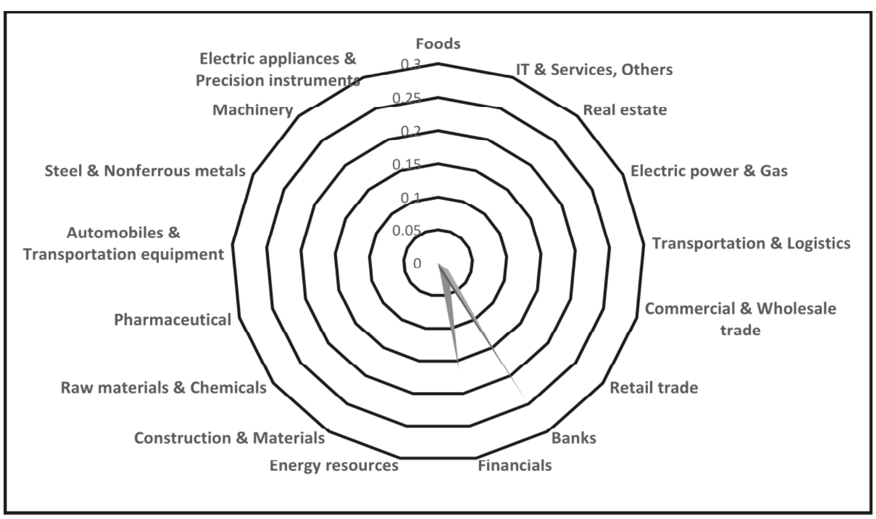
Figure 10: Accumulated Gains from TOPIX-17 Sectors under the Regret Minimization Model (VECM)



5.4.1. Results from the Multistep Decision-making Model Maximizing Expected Value (GARCH)

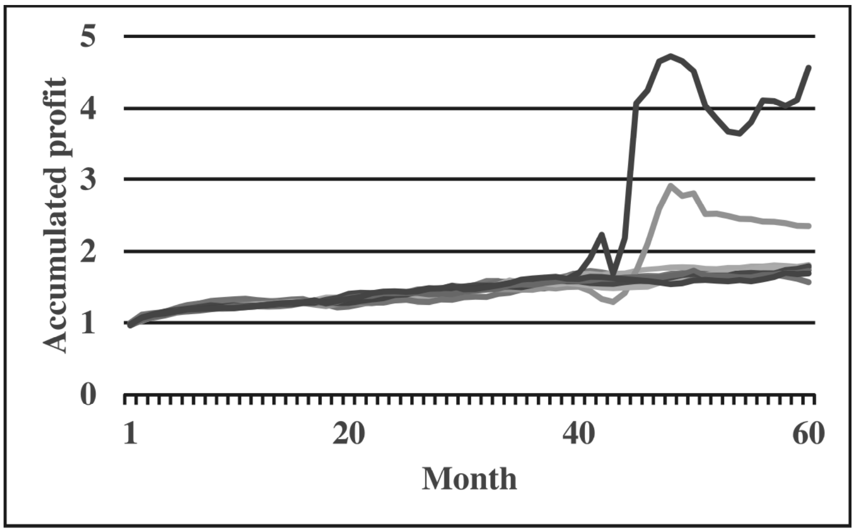
The accumulated value of TOPIX-17 indices is shown in Figure 11. The accumulated volume is concentrated in the Financials and Bankssectors. Under the expected value maximization model, the portfolio price increased by a

Figure 11: Accumulated Value of TOPIX-17 Indicesunder the Expected Value Maximization Model (GARCH)



maximum of 456.5% a minimum of 156.5%, and an average of 260.5% over five years.This case has generated the biggest gains found in this study because both sectors were modeled under the best suited condition and volatilities were expected to be small. Figure 12 shows the accumulation of gains over time; the large gains are due to the large random values.

Figure 12: Accumulated Gains from the TOPIX-17 Sectorsunder the Expected Value Maximization Model (GARCH)



5.4.2. *Results for the Multistep Decision-making Model Minimizing Regret (GARCH)*

The accumulated value of TOPIX-17 is shown in Figure 13. The accumulated value is concentrated in the Financials, Foods, IT& Services, and Transportation & Logisticssectors. Under the regret minimization model, the portfolio price increased by a maximum of 364.9%, a minimum of 131.2%, and an average of 212.2% over five years.Because portfolio purchases are made in a more risk-averse manner under this model than the expectedvalue maximization model, the tendency for large losses was not found. However, the average portfolio produced bigger gains when expected value was maximized than when regret was minimized, which suggests that maximizing expected value is more suitable when the world economy is stable.

6. CONCLUSION

In this research, we investigatedthe dynamic linkages among TOPIX-17 sector indices and 13 indicators that have a significant impact on the TOPIXand we

Figure 13: Accumulated Value of TOPIX Indicesunder the Regret Minimization Model (GARCH)

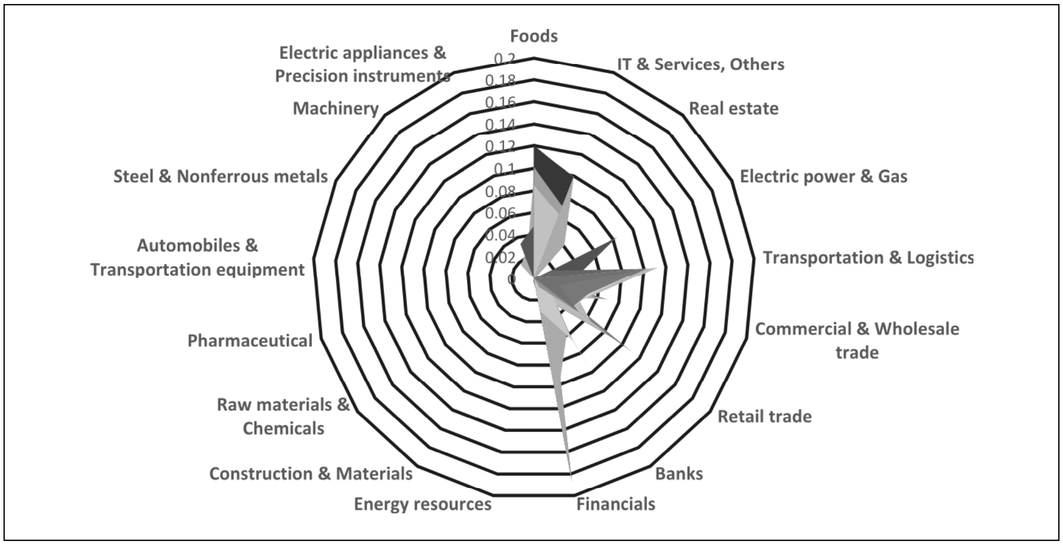
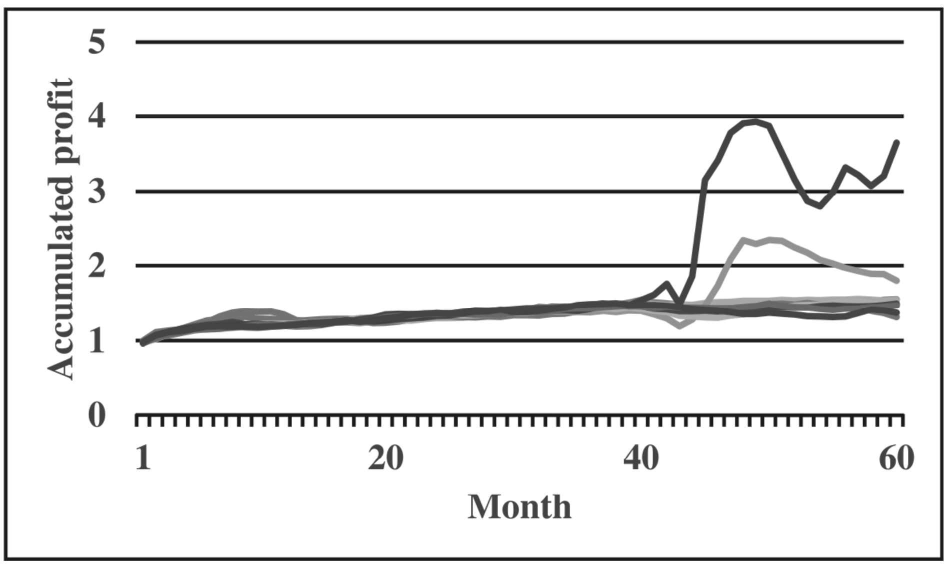


Figure 14: Accumulated Gains from TOPIX-17 Sectorsunder the Regret Minimization Model (GARCH)



examined two models for predicting portfolio prices in order to devise investment strategies. The results showed which indicators were affected to each TOPIX-17 index and how strongly they were affected. TOPIXwas shown to be especially strongly affected by FTSE and Dow, and the Transportation & Logistics, Foods, and Machinery sectors. When we predict the TOPIX-17 prices through using the VECM, prices tended to be more volatile than when we use GARCH. The GARCH results should be interpreted cautiously in consideration of outliers.

We developed optimal investment strategies on the basis of these prediction results. In particular, we applied multistep decision-makingmodelsthat maximized expected value and minimized regret. Using this method, we showed that is possible to create an optimal investment portfolio that minimizes the effect of variance by updating the strategy every 20 months. Compared with the regret minimization model, the expectedvalue maximizationmodel wouldproduce bigger gains in the average portfolio price. However, the expectedvalue maximizationmodel indicates a greater probability of incurring losses when the economy is unstable. Prices were more volatile in the VECM prediction than inthe GARCH prediction. Therefore, the accumulated value was dispersed to many variables. The above findings suggest that we need to consider thepossibility of losses. The regret minimizationmodel can reduce the risk of losses, but theexpected profit maydecrease. It should be noted that the decision-maker can benefit byhaving multiple ways tohandle various conditions.

In this paper, we have not touched upon the issues of selling short and trading commissions. These topics will be addressed in future research.

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