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The Predictability of Asian Stock Returns*

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This paper investigates the predictability of daily stock returns in twelve Asian countries. It pays attention to the forecasting variables rather than the forecasting models. The empirical results show that a simple model using the Dow Jones Index as a forecasting variable produces the smallest MSPE compared to the out-of-sample forecasting performance. According to the test results of Clark and West (2007), the difference of MSPE between this simple model and the random walk without drift is statistically significant at least at the 10 percent level for eight among twelve countries. In addition, the test results of Henriksson and Merton (1981) provide that this model is significantly superior in performance in directional accuracy of their forecasts for all countries.

JEL Classification: F31, F33
Keywords: MSPE, Clark and West test, directional accuracy, Henriksson and Merton test

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1. INTRODUCTION

Since the opening and the liberalization of capital and financial markets in the 1990s, developing countries' stock prices have been inclined to co-move with those of developed countries; moreover, their volatility has become bigger. These phenomena have been recently deepened in the aftermath of the global financial crisis.

In developing countries in which equity markets are neither open nor liberalized, their stock prices seem to be autoregressive because of the restrictions on information and government regulations and are chiefly influenced by domestic macroeconomic and financial variables. Their stock prices are not largely changed and can be predictable to some degree. However, as their equity markets open and become liberalized, their stock prices tend to be less autoregressive and increasingly affected by foreign economic and financial variables. Therefore, it becomes more difficult to predict their stock prices. On the other hand, the openness of equity markets in developing countries makes their stock prices co-move together with those of developed countries and thus, it may be possible to predict the former with the latter.[1] In short, in the 2000s, there exists a possibility that Asian developing countries' stock returns gradually follow a random walk or are influenced by foreign variables rather than domestic variables.

In 1995, as the World Trade Organization (WTO) was launched, the world has entered the era of free competition open to all. On the other hand, as a counterwork of globalization in the 1990s, a move towards regional economic associations has simultaneously come on the scene in various forms — EU, NAFTA, APEC, ASEAN, and so on. This move implies that stock prices may be influenced by regional as well as global economic variables. For example, since the 1997 currency crisis, Asian countries have tried to strengthen regional cooperation within the financial fields.

[1] International asset pricing or real business cycles literature shows that international stock markets' co-movement take place through the common worldwide discount factor or through terms of trade. See Pavlova and Rigobon (2007).

These kinds of efforts are expected to enable forecasting models, including regional financial variables, as explanatory variables in order to predict Asian stock returns.

Based on this recent trend in international equity markets, this study investigates the predictability of stock returns in twelve Asian countries. It analyzes which variables among the domestic, regional, and global variables do very well in the out-of-sample forecasting performance. The paper focuses on the forecasting variables rather than the forecasting models. In comparison to forecasting performance, this study also examines the directional accuracy of forecasts as well as the size of the forecast error.

The empirical results show that the individual model with a global or regional variable as an independent variable produces relatively smaller forecasting errors in out-of-sample performance comparisons for twelve Asian stock returns. In particular, the simple model using the Dow Jones Index as a forecasting variable has the smallest MSPE (mean square prediction error). According to the test results of Clark and West (2007), the difference of MSPE between this model and the driftless random walk is statistically significant at least at the 10% significant level for eight countries. Furthermore, the test results of Henriksson and Merton (1981) reveal that this model has a statistically significant excellence for predicting the correct direction of the stock return change in twelve Asian countries.

The subsequent sections of the paper are organized as follows. Section 2 reviews the references for the predictability of stock returns and compares the differences between this study and the references. Section 3 examines data characteristics, and section 4 discusses the forecasting models and techniques. In section 5 and section 6, the size of the forecast error and directional accuracy in forecasting models are compared, respectively. Section 7 summarizes and concludes this paper.

2. LITERATURE REVIEWS

Financial economists have continually investigated the predictability of stock returns in developed countries. Particularly, in the case of the U.S., a large number of studies showed that domestic macroeconomic and financial variables — for example, valuation ratios (Cochrane, 2008; Pástor and Stambaugh, 2009), nominal interest rates (Breen, Glosten, and Jagannathan, 1989; Ang and Bekaert, 2007), inflation rates (Fama and Schwert, 1977; Campbell and Vuolteenaho, 2004), term spreads (Campbell, 1987; Fama and French, 1989), and consumption-wealth ratio (Lettau and Ludvigson, 2001) — were valuable variables for predicting stock returns. However, according to Welch and Goyal (2008), this model's forecast was not significantly better than the historical average forecast which corresponds to the random walk with drift. On the other hand, Campbell and Thompson (2008) found that the former was superior to the latter in out-of-sample prediction when simple restrictions on regression coefficients and return forecasts were given. Rapach, Strauss, and Zhou (2010a) suggested that the individual model's forecasts were not superior to the historical average forecast, whereas the former's combination could outperform the latter.

In the 1990s, the well known papers which studied the predictability of stock returns in other countries besides the U.S. included the studies of Culter, Poterba, and Summers (1991), Harvey (1991), Bekaert and Hodrick (1992), Campbell and Hamao (1992), Ferson and Harvey (1993), and Solnik (1993). These papers had the within in-sample fit. As a recent study, Ang and Bekaert (2007) analyzed stock return predictability in the U.S., United Kingdom, Germany, and France. Hjalmarsson (2010) investigated which variables were good predictors for stock returns in 40 developed and developing countries. In out-of-sample analysis, Rapach, Strauss, and Zhou (2010b) found that U.S. stock returns were better than other economic variables for predicting stock returns in other developed countries.

As mentioned above, many papers have been published for the predictability of stock returns until now. Yet, most of these papers analyzed only the developed countries including the U.S. They also used low frequency data, such as monthly domestic financial and economic variables, in the analysis for forecasting the performance of stock returns. Hence, by using high frequency data, this paper analyzes stock return predictability in Asian countries, which has not been investigated much until now, even though Asian equity markets have been rapidly developed and expanded since the 1990s.[2)] It also tests whether or not foreign financial variables as well as domestic variables are good predictors for Asian stock returns.

To put it concretely, the paper compares out-of-sample performance using nominal interest rates, exchange rates, and stock returns discussed in references which are mentioned above. Since daily data are used in this paper, however, low frequent variables, such as valuation ratios, inflation rates, and consumption-wealth ratios cannot be considered. According to a suggestion of Rapach, Strauss, and Zhou (2010b), the U.S. stock returns are also together investigated. In addition, based on the empirical results of Campbell and Thompson (2008) and Rapach, Strauss, and Zhou (2010a), this paper utilizes simple restrictions on regression coefficients as well as return forecasts and simple model's combination.

3. DATA

In this paper, daily stock returns of twelve Asian countries, including five ASEAN countries — Australia, China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand — are considered for a comparison of out-of-sample forecasting performance.[3)] Stock price indices used in the paper are All Ordinaries (Australia), Shanghai Composite (China), Hang Seng (Hong Kong), Bombey Sensitive 30 (India), Jakarta Composite (Indonesia), Nikkei 205 (Japan), Seoul Composite

[2)] Some papers documented the profitability of momentum investment strategy using daily or Asian stock returns. See Patro and Wu (2004) for daily data, and Hameed and Kusnadi (2002) for the Asian stock data.

[3)] Indonesia, Malaysia, Philippines, Singapore, and Thailand are ASEAN member countries.

(Korea), KLSE Composite (Malaysia), PSE Composite (Philippines), Straits Times (Singapore), Taiwan Weighted (Taiwan), SET (Thailand), and Dow Jones 30 Industrials (U.S.).[4)] They are the daily closing stock prices. The sample period is from January 4, 1999 to February 28, 2011, and the sample size is 2,966.

Figures 1 to 12 plot twelve Asian stock price indices, when the stock price of January 4, 1999 (which is the base date) is converted into 100. Asian stock prices, which rose in the early sample period, consistently dropped due to the collapse of the IT bubble in the early 2000s along with the September 11 terrorist attacks in 2001. In 2003, the stock prices changed directions because of each country's monetary and fiscal expansion policies for overcoming the economic recession. The prices persistently went up until October 2007. However, as the global financial crisis took place, Asian stock prices plummeted starting from November 2007. After many countries carried out their cooperative expansion policies, stock prices slowly began to rise again. These figures show that stock prices in Asian countries repeatedly rose and fell in a similar pattern.[5)]

The paper considers one lagged domestic, regional, and global financial variables as out-of-sample forecasting variables for predicting stock returns in Asian countries. Their own stock prices and exchange rates (local currency/$) are used as domestic variables.[6)]

As regional variables, the paper uses the weighted Asian stock price indices, which are derived from multiplying each stock price by its (dollar or PPP) GDP weight and stock market capitalization weight of the twelve Asian countries, respectively. It also considers the weighted Asian exchange rates, which are obtained from multiplying each exchange rate by the same

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[4)] Take a look at Appendix for a short description on the thirteen stock indices analyzed in the paper.

[5)] Observe table A1 for autocorrelation coefficients among Dow Jones stock returns at time t-1, and twelve Asian stock returns at time t.

[6)] Domestic interest rates are also considered. However, their out-of-performance is not reported because it is worse than that of using domestic stock returns or local exchange rates.

Figure 1 Australia

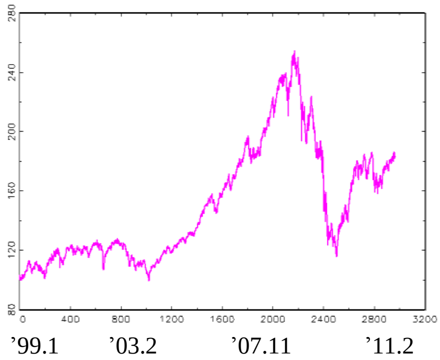


Figure 2 China

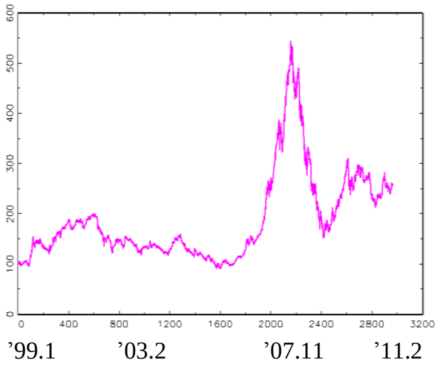


Figure 3 Hong Kong

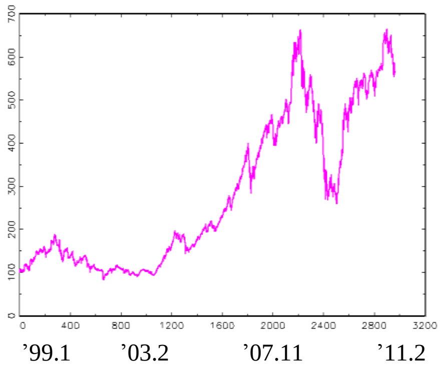


Figure 4 India

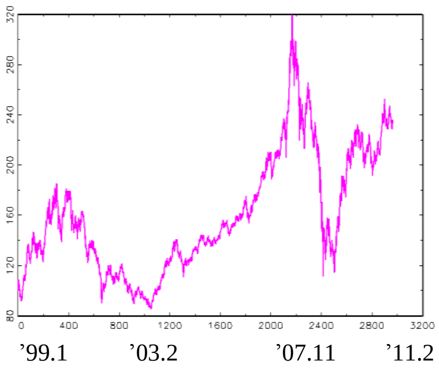


Figure 5 Indonesia

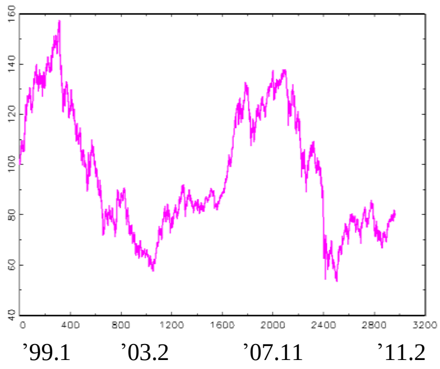


Figure 6 Japan

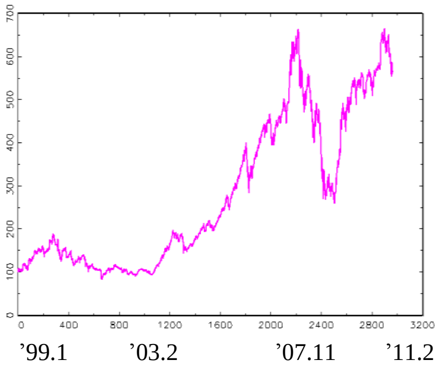


Figure 7 Korea

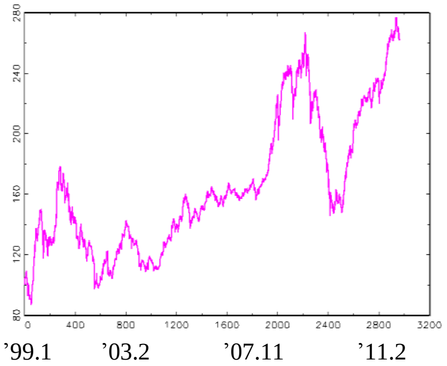


Figure 8 Malaysia

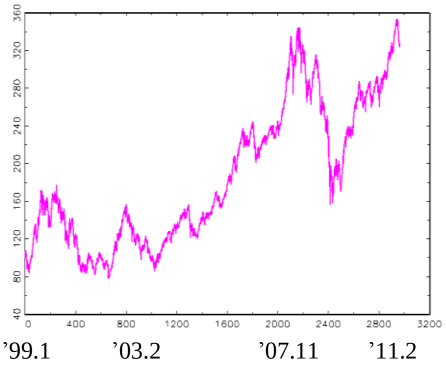


Figure 9 Philippines

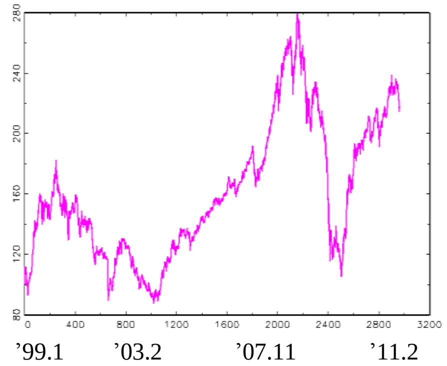


Figure 10 Singapore

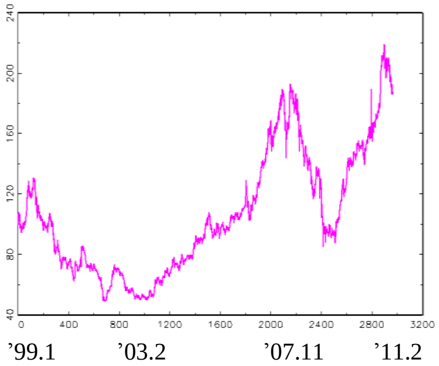


Figure 11 Taiwan

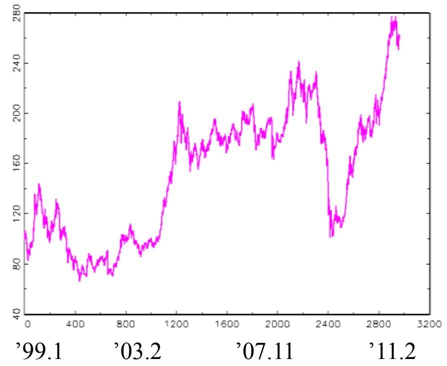


Figure 12 Thailand

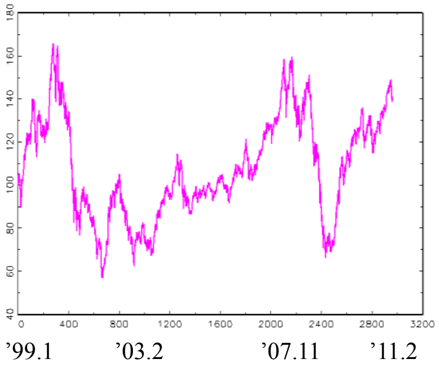


Figure 13 Dollar GDP Weighted

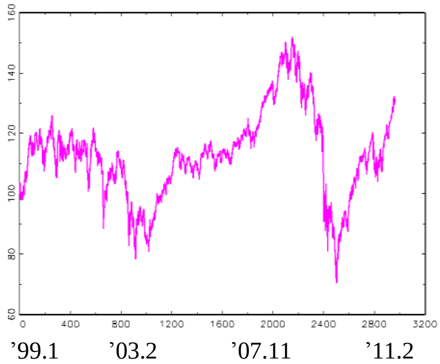


Figure 14 Dow Jones

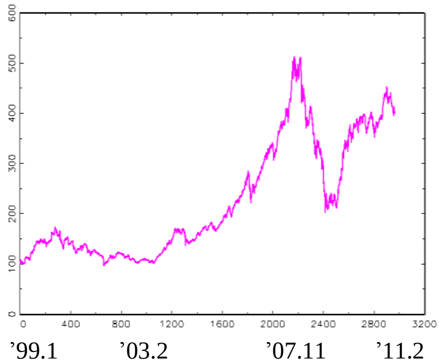


Figure 15 ¥/$

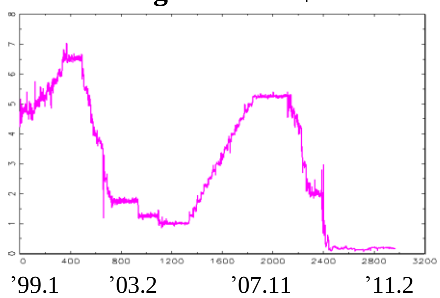
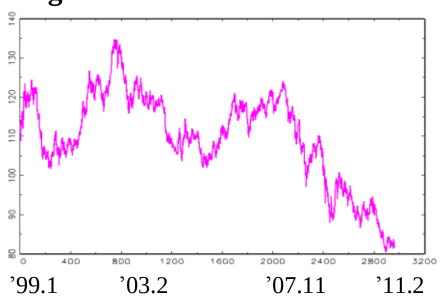


Figure 16 Federal Funds Rate



weights used in deriving the weighted Asian stock price indices.[7] Figure 13 shows the weighted Asian stock price indices which are derived from multiplying each country’s stock price by its dollar GDP weight. The other weighted Asian stock price indices obtained by using PPP GDP and stock market capitalization weights are not described to save space because they show a similar pattern with figure 13. The Dow Jones Index, ￥/$ exchange rates, and federal funds rates are considered as global financial variables. Figure 14 plots the movement of the Dow Jones Index. It repeatedly goes up and down in a similar pattern of Asian stock price indices. The movement of ￥/$ exchange rates is shown in figure 15. ￥/$

[7] The International Monetary Fund (IMF) and the Asian Development Bank (ADB) are the source of dollar GDP (or PPP GDP) and stock market capitalization data, respectively. The other data are obtained from Thompson Reuters’ Datastream database.

exchange rates and the Dow Jones Index move in the same direction between the mid-2000s and early 2009. The movement of federal funds rates is depicted in figure 16. Federal funds rates move in the same way with the Dow Jones Index until early 2009, depending on the business cycle.

3.1. Summary Statistics

Each country's stock price index has a unit root, but the indices are typically not cointegrated with the explanatory variables. The paper therefore uses percentage stock returns which are multiplied by 100 after the log difference of stock prices. Table 1 lists the basic statistics on them.

On average, stock returns have positive values over the whole sample period in all countries except for Japan. However, only for India and Indonesia, they are statistically significant at the 10% and 5% levels, respectively. The standard deviation in Korea is 1.878 which is the biggest among the twelve countries. This results from the fact that Korea has entirely opened its stock market in 1998 just after the currency crisis. On the other hand, the standard deviation is unexpectedly the smallest in Australia at 1.027. This difference may imply that Australia is not deeply affected by the recent global financial crisis.

The skewness has negative values for the eleven countries with the exception of Philippines. This means that the distributions of the stock returns have a tilt to the left of the average. In all countries, the kurtosis is greater than 3 which is a normal distribution's kurtosis. It is relatively greater for ASEAN countries. In most countries, the absolute minimum values are generally greater than the maximum values. However, they are relatively smaller in Australia. In table 1, $Q(10)$ shows the Ljung-Box test statistics for the 10th order correlation in stock returns. The null hypothesis of no 10th order correlation is statistically rejected at least at the 5% significant level in other countries except Australia and Singapore. This may suggest that autoregressive models outperform other models — for example, the random walk without drift or with drift — in out-of-sample

Table 1 Summary Statistics for Stock Returns

Countries	Mean	Standard Deviation	Skewness	Kurtosis	Maximum Value	Minimum Value	$Q(10)$
Australia	0.020	1.027	–0.862	11.993	5.360	–9.486	11.404
China	0.032	1.698	–0.039	6.998	9.401	–9.256	28.412**
Hong Kong	0.029	1.686	–0.139	10.497	13.407	–13.582	29.017**
India	0.058+	1.814	–0.405	12.656	15.990	–17.184	26.745**
Indonesia	0.072*	1.627	–0.630	11.001	11.491	–13.602	38.769**
Japan	–0.007	1.589	–0.287	9.212	13.235	–12.111	27.691**
Korea	0.040	1.878	–0.544	8.014	11.284	–16.115	18.872*
Malaysia	0.033	1.065	–1.144	18.146	5.850	–13.250	81.077**
Philippines	0.021	1.528	0.523	26.525	18.926	–15.151	24.629**
Singapore	0.026	1.377	–0.729	12.695	7.531	–15.517	14.277
Taiwan	0.011	1.614	–0.426	7.554	9.716	–12.778	22.300*
Thailand	0.032	1.626	–0.975	18.489	10.577	–20.340	19.799*

Notes: 1) $Q(10)$ implies Ljung-Box test statistics for the 10th order correlation in stock returns.
2) +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

forecasting analysis. Yet, we cannot rule out the possibility that high autocorrelation of stock returns may be a phenomenon which is greatly exaggerated as a result of the global financial crisis.

3.2. In-sample Fit Results

The paper first investigates which forecasting variables well explain Asian stock returns in in-sample estimation before analyzing out-of-sample forecasting performance.[8)] Since the difference in out-of-sample performance chiefly depends on the forecasting variables rather than the forecasting models, as discussed in the next section, the paper concentrates on only the following simple model.

8) Inoue and Kilian (2004) argued that in-sample tests had higher power than out-of-sample tests in many cases.

Table 2 In-Sample Estimation Results of β_1

	Domestic Variables		Regional Variables		Global Variables		
	SR	ER	\$GDP	SMC	DJ	YEN	FFR
Australia	–0.024 (0.018)	0.120 (0.021)**	0.064 (0.014)**	0.063 (0.014)**	0.413 (0.013)**	0.175 (0.027)**	–0.635 (0.172)**
China	–0.005 (0.018)	0.789 (0.393)*	0.053 (0.024)*	0.045 (0.023)+	0.135 (0.024)**	0.050 (0.045)	–0.977 (0.285)**
Hong Kong	–0.021 (0.018)	0.177 (0.035)**	0.029 (0.023)	0.021 (0.023)	0.498 (0.022)**	0.216 (0.045)**	–1.133 (0.283)**
India	0.028 (0.018)	–0.181 (0.093)+	0.027 (0.025)	0.022 (0.025)	0.258 (0.025)**	0.112 (0.048)*	–1.031 (0.304)**
Indonesia	0.104 (0.018)**	–0.103 (0.029)**	0.153 (0.022)**	0.143 (0.022)**	0.306 (0.023)**	0.120 (0.043)**	–1.242 (0.273)**
Japan	–0.008 (0.018)	0.406 (0.042)**	0.133 (0.022)**	0.130 (0.022)**	0.531 (0.021)**	0.406 (0.042)**	–1.136 (0.266)**
Korea	0.036 (0.018)+	–0.164 (0.048)**	0.081 (0.026)**	0.081 (0.026)**	0.462 (0.025)**	0.244 (0.050)**	–1.225 (0.315)**
Malaysia	0.138 (0.018)**	–0.153 (0.060)*	0.091 (0.015)**	0.087 (0.015)**	0.210 (0.015)**	0.094 (0.028)**	–0.461 (0.179)*
Philippines	0.062 (0.018)**	–0.385 (0.055)**	0.190 (0.021)**	0.184 (0.021)**	0.394 (0.021)**	0.222 (0.040)**	–0.978 (0.256)**
Singapore	0.033 (0.018)+	–0.135 (0.079)+	0.019 (0.019)	0.009 (0.019)	0.341 (0.019)**	0.159 (0.037)**	–1.044 (0.231)**
Taiwan	0.036 (0.018)+	–0.416 (0.107)**	0.158 (0.022)**	0.151 (0.022)**	0.348 (0.022)**	0.177 (0.043)**	–0.715 (0.271)**
Thailand	0.010 (0.018)	–0.230 (0.066)**	0.050 (0.023)*	0.041 (0.022)+	0.260 (0.023)**	0.077 (0.043)+	–0.357 (0.273)

Notes: 1) SR, ER, DJ, YEN, and FFR use local stock returns, local exchange rate changes, Dow Jones stock returns, ¥/\$ changes, and federal funds rate changes as a regressor, respectively. 2) \$GDP and SMC use Asian weighted stock returns obtained from dollar GDP and stock market capitalization weights as a regressor, respectively. 3) $^{+}$, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

$$y_t = \beta_0 + \beta_1 x_{t-1} + \varepsilon_t, \quad t = 1,\ 2,\ \ldots,\ T, \tag{1}$$

where y_t is each country's percentage stock return at time *t*, and x_{t-1} implies one variable among one lagged domestic, regional, and global variables. Domestic variables cover each country's stock returns (SR) and exchange rate changes (ER). Regional variables include the weighted Asian stock price indices, which are derived from multiplying each stock price by its dollar GDP weight ($GDP) and stock market capitalization weight (SMC), in twelve Asian countries, respectively.[9] The Dow Jones stock returns (DJ), ￥/$ exchange rate changes (YEN), and federal funds rate changes (FFR) are used as global financial variables.

In-sample estimation results of univariate regressions on individual forecasting variables over the whole sample period are presented in table 2. The estimates of β_0 in equation (1) are not statistically significant in other countries except in India and Indonesia. Therefore, table 2 shows the estimates of β_1 when $y_t = \beta_1 x_{t-1} + \varepsilon_t$ is estimated instead of equation (1). When one lagged own stock returns (SR) are used as explanatory variables, the estimates of β_1 are negative values and are statistically significant at least at the 10% level for Indonesia, Korea, Malaysia, Philippines, Singapore, and Taiwan. The estimates of β_1 for one lagged exchange rate changes (ER) are also statistically significant in all countries, but the signs of estimates depend on the countries. The regional variables ($GDP and SMC) also have a statistically significant explanation for stock returns in other Asian countries except in Hong Kong, India, and Singapore. In all countries, the estimates of β_1 for one lagged Dow Jones stock returns (DJ) as a global financial variable are greater and statistically more significant than those for one lagged own stock returns (SR). One lagged ¥/$ exchange rate changes (YEN) also provide a statistically significant explanation for stock returns in all countries but China. Positive federal funds rate changes significantly push down stock returns in all countries.

In summary, in-sample fit results reveal that the models including the global variables as explanatory variables produce significantly good explanation for the twelve Asian stock returns. In particular, among the estimation models, the model without an intercept using the Dow Jones Index as an explanatory variable has the most significant and biggest estimates of β_1.

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[9] Table 2 doesn't contain the case of PPP GDP, because it doesn't outperform the case of the dollar GDP in out-of sample performance. The cases of the weighted Asian exchange rates derived in the similar way with stock returns are also omitted, because these cases are not superior to those of the weighted stock price indices.

4. OUT-OF-SAMPLE FORECASTING MODELS AND TECHNIQUES

This section discusses which forecasting models and techniques are used in out-of-sample forecasting analysis.

4.1. Forecasting Models

The random walk model with no drift is considered as the benchmark forecasting model. As already mentioned in literature reviews, the historical average forecast, which corresponds to the random walk with drift, is used as a benchmark in the U.S. stock market prior to the global financial crisis. In this study, however, average returns are not significantly different from zero for the other countries except for India and Indonesia, as already displayed in table 1. The random walk model without drift (RW) also outperforms the random walk model with drift in a one-step-ahead out-of-sample forecasting analysis. The random walk without drift forecast of stock returns is simply equal to zero at each point in time.[10)]

The paper uses equation (1), without an intercept, as a linear forecasting model in most cases, because in linear AR (*p*) and VAR (*p*) models, the case of $p=1$ outperforms the cases of $p>1$. Moreover, the models excluding its own lagged variables are relatively good in out-of-sample performance. In equation (1), out-of-sample performance in case of $\beta_0 = 0$ is superior to that in the case of $\beta_0 \neq 0$ for all countries. The forecasting regression without an intercept is then the clear analogue of the random walk without

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[10)] According to the efficient market hypothesis, $E(p_{t+1}|I_t) = p_t \cdot p_{t+1}$ is the logarithm of stock price at time $t+1$, and I_t is an information set at time *t*. The random walk without drift implies that $p_{t+1} = p_t + \varepsilon_{t+1}$, $E(\varepsilon_{t+1}|I_t) = 0$, $Var(\varepsilon_{t+1}|I_t) = \sigma^2$, and $Cov(\varepsilon_{t+i},\ \varepsilon_{t+j}|I_t) = 0$. From the rational expectations model, it is also easily derived that the best predictor of tomorrow's exchange rate (e_t) is today's exchange, that is, $E(e_{t+1}|I_t) = e_t$. Since Meese and Rogoff (1983), it is well known that any structural and time series models cannot outperform the random walk model in developed foreign exchange markets. See literature reviews for stock markets (see Chancharat and Valadkhani (2007) for the random walk test in Asian stock markets).

drift. It also investigates whether or not the predictive power of equation (1) is improved by using locally weighted regression (LWR). Diebold and Nason (1990) found that the forecasting performance of LWR was better than that of linear autoregressive models.

4.2. Forecasting Techniques

Out-of-sample forecasts are begun at the 501th observation for predicting long periods and therefore, the period from January 6, 1999 to January 17, 2001 (sample size=500) is used for the first in-sample fit. The period from January 18, 2001 to February 28, 2011 is reserved for out-of-sample forecast comparison.

The paper carries out out-of-sample prediction with two techniques — the rolling and adding sample techniques.[11)] The procedure in the rolling sample technique (R) for one-day-ahead prediction is as follows: First, the stock returns on January 18, 2001 are forecasted using their estimates, after the forecasting models are estimated over the period from January 6, 1999 to January 17, 2001. Second, stock returns on January 19, 2001 are forecasted using their estimates, after the forecasting models are estimated over the period from January 7, 1999 to January 18, 2001, and so forth. Lastly, stock returns on February 28, 2011 are forecasted, after this procedure is repeated 2,462 times. In short, we recursively estimate $E(y_{501}|y_{500}, \ldots, y_1)$ and then $E(y_{502}|y_{501}, \ldots, y_2)$, and the like. This procedure is continued until the reserved sample is exhausted which then gives rise to a sequence of 2,463 ex ante one-day-ahead forecasts.

As the sample size used in in-sample estimation is bigger, it contains more information, whereas it may be less stationary. Hence, it is not easy to recognize the optimal sample size and the impact of the sample size on prediction in advance. To alleviate this problem, we also consider adding sample technique (A) in which the sample size expands as additional

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[11)] Clark and West (2007) called the rolling and adding sample techniques rolling and recursive schemes, respectively.

observations are supplemented. The procedure in adding the sample technique is summarized as follows: First, in the same way with the rolling sample technique, the stock returns on January 18, 2001 are forecasted using their estimates, after the forecasting models are estimated for the period from January 6, 1999 to January 17, 2001. Second, stock returns on January 19, 2001 are forecasted using their estimates, after the forecasting models are estimated for the period from January 6, 1999 to January 18, 2001. That is, we successively estimate $E(y_{501}|y_{500}, \ldots, y_1)$ and then $E(y_{502}|y_{501}, \ldots, y_1)$. This procedure is continued until the last reserved sample period from January 6, 1999 to February 28, 2011 is exhausted which then produces a sequence of 2,463 one-day-ahead forecasts.

5. COMPARISON OF THE FORECAST ERROR

For comparison of the forecast error's size in a one-step-ahead prediction, the paper calculates the following MSPE (mean square prediction error) from the forecasting models.

$$\text{MSPE} = \sum_{k=1}^{2463} [y_{T+k} - \hat{y}_{T+k}]^2 / 2,463. \qquad (2)$$

Where y_{T+k} and $\hat{y}_{T+k}$ are actual and forecasting values of the percentage stock returns at time $T+k$ (T=500), respectively. Table 3 contains a one-step-ahead out-of-sample MSPE, when local, regional, and global variables are individually considered as explanatory variables in equation (1). R and A in table 3 indicate the rolling and adding sample techniques, respectively. The letters 1 to 5 on the upper right corner of MSPE represent the rank of models in out-of-sample forecasting performance.

The forecasting results show that the models using global or regional variables as forecasting variables have relatively smaller out-of-sample MPSE.

Table 3 Out-of-Sample MSPE Using the Univariate Regression without an Intercept

		Domestic Variables		Regional Variables		Global Variables			RW
		SR	EX	$GDP	SMC	DJ	YEN	FFR	
Australia	R	1.131	1.116^{4}	1.115^{3}	1.117^{5}	0.799^{1}	1.099^{2}	1.128	1.125
	A	1.127	1.114^{3}	1.118^{4}	1.119^{5}	0.819^{1}	1.109^{2}	1.123	1.125
China	R	2.986	3.533	2.976^{5}	2.979	2.935^{1}	2.962^{2}	2.968^{3}	2.976^{4}
	A	2.980	3.006	2.973^{3}	2.975^{4}	2.943^{1}	2.980	2.969^{2}	2.976^{5}
Hong Kong	R	2.743	2.726^{3}	2.743	2.746	2.374^{1}	2.688^{2}	2.727^{4}	2.731^{5}
	A	2.738	2.711^{3}	2.736	2.736	2.370^{1}	2.708^{2}	2.720^{4}	2.731^{5}
India	R	3.070	3.067^{5}	3.072	3.074	2.941^{1}	3.061^{4}	3.053^{2}	3.055^{3}
	A	3.057	3.071	3.059^{5}	3.060	2.953^{1}	3.054^{2}	3.057^{4}	3.055^{3}
Indonesia	R	2.373^{3}	2.400	2.367^{2}	2.379^{4}	2.226^{1}	2.384^{5}	2.401	2.391
	A	2.361^{3}	2.393	2.358^{2}	2.368^{4}	2.240^{1}	2.385^{5}	2.394	2.391
Japan	R	2.682	2.551^{2}	2.631^{4}	2.638^{5}	2.102^{1}	2.551^{2}	2.665	2.671
	A	2.675	2.583^{2}	2.637^{4}	2.639^{5}	2.148^{1}	2.583^{2}	2.659	2.671
Korea	R	2.759	2.744^{4}	2.742^{3}	2.745	2.489^{1}	2.728^{2}	2.745^{5}	2.749
	A	2.754	2.739^{4}	2.740^{5}	2.742	2.505^{1}	2.719^{2}	2.737	2.749
Malaysia	R	0.847^{4}	0.857	0.843^{2}	0.846^{3}	0.799^{1}	0.858^{5}	0.859	0.858
	A	0.842^{2}	0.863	0.843^{3}	0.845^{4}	0.791^{1}	0.856^{5}	0.858	0.858
Philippines	R	2.327	2.279^{5}	2.219^{2}	2.234^{3}	1.981^{1}	2.245^{4}	2.310	2.300
	A	2.308	2.288^{5}	2.228^{2}	2.234^{3}	2.023^{1}	2.275^{4}	2.305	2.300
Singapore	R	1.781^{5}	1.774^{3}	1.783	1.782	1.622^{1}	1.772^{2}	1.784	1.776^{4}
	A	1,779	1.776^{5}	1.777	1.777	1.624^{1}	1.766^{2}	1.776^{4}	1.776^{3}
Taiwan	R	2.320	2.319	2.282^{2}	2.290^{3}	2.090^{1}	2.298^{4}	2.313^{5}	2.316
	A	2.317	2.309^{5}	2.275^{2}	2.280^{3}	2.092^{1}	2.300^{4}	2.310	2.316
Thailand	R	2.344	2.299^{3}	2.304^{5}	2.309	2.214^{1}	2.299^{2}	2.310	2.302^{4}
	A	2.309	2.292^{2}	2.301^{3}	2.302^{5}	2.210^{1}	2.302^{4}	2.304	2.302

Notes: 1) SR, ER, DJ, YEN, and FFR use local stock returns, local exchange rate changes, Dow Jones stock returns, ¥/$ changes, and federal funds rate changes as a forecasting variable, respectively. 2) $GDP and SMC use Asian weighted stock returns obtained from dollar GDP and stock market capitalization weights as a forecasting variable, respectively. 3) RW implies the random work without drift. 4) R and A indicate the rolling and adding of sample techniques, respectively. 5) Numbers in the upper-right corner of MSPE show the rank of models.

Particularly, the Dow Jones Index, ¥/$ exchange rates, and Asian weighted stock price indices in turn have a better forecasting power. Table 3 also shows that only those models using the Dow Jones Index have a smaller MPSE than the random walk with no drift for all countries. The models with domestic variables as forecasting variables are inferior to the random walk without drift in most countries. The random walk without drift generally outperform the random walk with drift compared to out-of-sample MSPE and therefore, the latter's MSPE is not reported in table 3 in order to save space.

When the Dow Jones Index is used, the rolling sample technique's out-of-sample MSPE is smaller than that of the adding sample technique for Australia, China, India, Indonesia, Japan, Korea, Philippines, Singapore, and Taiwan. Meanwhile, the reverse is the truth for Hong Kong, Malaysia, and Thailand.

In table 3, we confirm that stock returns in Asian countries can be well predicted using equation (1) with the Dow Jones Index as an explanatory variable.[12] Table 4 shows whether or not each country's stock returns can be better predicted by the models, which are more complicated than linear equation (1), or which include the Dow Jones Index as one of the two explanatory variables. In table 4, DJ-YEN implies the case that one lagged Dow Jones stock returns and ¥/$ exchange rate changes are used together as forecasting variables. The predictability of ¥/$ exchange rates is relatively good, as already displayed in table 3. DJ2 shows the case where one and two lagged Dow Jones stock returns are considered together. In LWR-DJ, we estimate equation (1) with the Dow Jones Index as an explanatory variable by the locally weighted regression (LWR). According to Diebold and Nason (1990), LWR has better forecast than linear autoregressive models for predicting the exchange rates of developed countries.[13]

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[12] In addition, the paper compares a case of sample size 1,000. The empirical results are not changed. See table A2.

[13] Diebold and Nason (1990) and Meese and Rose (1991) respectively compared out-of-sample forecasting performance in time series and structural exchange rate models using LWR.

Table 4 Out-of-Sample MSPE Using Extended DJ Models

		DJ	DJ-YEN	DJ2	LWR-DJ	CT1-DJ	CT2-DJ	RW
Australia	R	0.799^{2}	0.802^{4}	0.802^{5}	0.795^{1}	0.799^{2}	1.016	1.125
	A	0.819^{3}	0.820^{5}	0.819^{2}	0.814^{1}	0.819^{3}	1.008	1.135
China	R	2.935^{3}	2.934^{2}	2.947^{4}	2.953^{5}	2.933^{1}	2.987	2.976
	A	2.943^{2}	2.948^{5}	2.946^{4}	2.944^{3}	2.942^{1}	2.969	2.976
Hong Kong	R	2.374^{1}	2.380^{3}	2.398^{5}	2.384^{4}	2.374^{1}	2.613	2.731
	A	2.370^{2}	2.375^{5}	2.373^{4}	2.366^{1}	2.370^{2}	2.601	2.731
India	R	2.941^{1}	2.955^{4}	2.945^{3}	2.956^{5}	2.941^{1}	3.033	3.055
	A	2.953^{3}	2.957^{5}	2.946^{2}	2.945^{1}	2.953^{3}	3.025	3.055
Indonesia	R	2.226^{3}	2.237^{5}	2.226^{2}	2.222^{1}	2.226^{3}	2.343	2.391
	A	2.240^{3}	2.242^{5}	2.238^{2}	2.226^{1}	2.240^{3}	2.339	2.391
Japan	R	2.102^{2}	2.091^{1}	2.104^{5}	2.102^{2}	2.102^{2}	2.431	2.671
	A	2.148^{2}	2.125^{5}	2.146^{1}	2.153^{4}	2.148^{2}	2.441	2.671
Korea	R	2.489^{1}	2.491^{4}	2.496^{5}	2.489^{1}	2.489^{1}	2.659	2.749
	A	2.505^{4}	2.504^{2}	2.500^{2}	2.503^{1}	2.505^{4}	2.672	2.749
Malaysia	R	0.799^{2}	0.802^{4}	0.799^{1}	0.803^{5}	0.799^{2}	0.846	0.858
	A	0.791^{3}	0.792^{5}	0.789^{2}	0.787^{1}	0.791^{3}	0.836	0.858
Philippines	R	1.981^{2}	1.978^{1}	1.983^{5}	1.982^{4}	1.981^{2}	2.182	2.300
	A	2.023^{3}	2.023^{2}	2.025^{5}	2.017^{1}	2.023^{3}	2.183	2.300
Singapore	R	1.622^{1}	1.629^{5}	1.627^{4}	1.623^{3}	1.622^{1}	1.755	1.776
	A	1.624^{3}	1.625^{5}	1.619^{2}	1.615^{1}	1.624^{3}	1.742	1.776
Taiwan	R	2.090^{2}	2.095^{4}	2.088^{1}	2.096^{5}	2.090^{2}	2.218	2.316
	A	2.092^{3}	2.092^{5}	2.084^{1}	2.089^{2}	2.092^{3}	2.215	2.316
Thailand	R	2.214^{2}	2.221^{5}	2.219^{4}	2.209^{1}	2.214^{2}	2.295	2.302
	A	2.210^{3}	2.213^{5}	2.209^{2}	2.204^{1}	2.210^{3}	2.283	2.302

Notes: 1) DJ-YEN uses Dow Jones stock returns and ¥/$ changes as forecasting variables. 2) DJ2 uses one and two lagged Dow Jones stock returns as forecasting variables. 3) LWR-DJ estimates DJ by locally weighted regression. 4) CT1-DJ and CT2-DJ use positive slope and forecast constraints of Campbell and Thompson (2008), respectively. 5) RW implies the random work without drift. 6) R and A indicate the rolling and adding sample techniques, respectively. 7) Numbers in the upper-right corner of MSPE show the rank of models. 8) A smoothing constant λ is assumed to equal to 1 in LWR-DJ.

This paper considers the case of $p=1$ which is widely used in a polynomial regression of degree p of y_t on x_{t-1}. We assume $q=\text{int}(\lambda \times T)$, where $\text{int}(\cdot)$ is round down to the nearest integer. T is the sample size and λ is a smoothing constant such that $0<\lambda<1$. After the x_t's are ranked as $x_i^1, x_i^2, x_i^3, \ldots, x_i^q$ by Euclidean distance from $x_i (t=1, \ldots, T)$, the neighbor weight function is formed by using this Euclidean distance from x_i to its qth closest neighbor. That is, let $w_t(x_i)$, for $t=1$ to T, be set of weights for the points (x_t, y_t) defined by

$$w_t(x_i) = W(d(x_i, x_t)/d(x_i, x_i^q)), \tag{3}$$

where $W(\cdot)$ is the tricube function. Then the estimator is linear in y_t.

$$\hat{y}_i = \hat{m}(x_i) = \textstyle\sum_{t=1}^{T} \phi_t(x_i) y_t, \quad i=1, \ldots, T, \tag{4}$$

where $\phi_t(x_i) = x_i^* \left[\sum_{t=1}^{T} w_t(x_i) x_t^{*\prime} x_t^*, \right]^{-1} w_t(x_i) x_t^{*\prime}, \quad x_i^* = \{1, y_{i-1}\}$.

When the number of the nearest neighbors is equal to T, the nearest neighbor estimate becomes the average of the dependent variable. However, this is not the case with the LWR. The observations are still weighted in the LWR. x_i is replaced with x_{T+1} in one-step-ahead out-of-sample forecasting. Table 4 shows only the case of $\lambda=1$ that is chosen generally.

CT1-DJ and CT2-DJ use the positive slope and forecast constraints of Campbell and Thompson (2008), respectively. That is, in CT1-DJ, whenever an estimate of β_1 is negative, β_1 is assumed to be zero in out-of-sample forecasting analysis. Similarly, in CT2-DJ, whenever the forecast is negative, it is set to be zero. Out-of-sample MSPE of CT1-DJ is the same as that of DJ in all countries but China. This implies that the estimates of β_1 in DJ are all positive in all countries except China. Yet, the restriction of CT2-DJ does not improve the out-of-sample performance of

DJ.[14)]

The empirical results indicate that DJ-YEN or DJ2 cannot outperform DJ in out-of-sample forecasting performance, even if the former may be superior to the latter in in-sample fit. CT1-DJ and CT2-DJ cannot also beat DJ. On the other hand, LWR-DJ, the nonparametric model, has a smaller out-of-sample MSPE than DJ, the linear parametric model, in some cases. But, even in these cases, the difference of MSPE between the two models is small. Besides, in real prediction, λ should be also chosen. In this study, the forecasting superiority of LWR depends on the choice of λ in all cases. Hence, the subsequent topics are discussed with only linear models in order to avoid complexity.

Until now, the empirical results show that the simple model with the Dow Jones Index as an explanatory variable has a smaller MPSE than the other complex models, and the random walk without drift (RW) in a one-step-ahead out-of-sample forecasting analysis. From now, the tests of Clark and West (2005, 2007) are carried out in order to examine whether the difference of MSPE between the simple model with the Dow Jones Index and the random walk without drift is statistically significant or not. When forecasts from the nested models are compared, the Diebold and Mariano (1995) test statistic has a non-standard asymptotic distribution. In order to correct this fundamental error, Clark and West's modified statistic is used as follows:

$$\begin{aligned}
\mathrm{CW} &= \left[\hat{\sigma}^2_{RW} - (\hat{\sigma}^2_{DJ} - adj)\right] / SE, \\
\hat{\sigma}^2_{RW} &= \sum (y_{T+\tau} - \hat{y}_{RWT,T+\tau})^2 / (2464 - \tau), \\
\hat{\sigma}^2_{DJ} &= \sum (y_{T+\tau} - \hat{y}_{DJT,T+\tau})^2 / (2464 - \tau), \\
adj &= \sum (\hat{y}_{RWT,T+\tau} - \hat{y}_{DJT,T+\tau})^2 / (2464 - \tau).
\end{aligned} \tag{5}$$

[14)] These restrictions on the other variables, such as $GDP, SMC, and FFR, improve their out-of-sample performance in many cases.

Table 5 Clark and West Test (R)

Forecasting Period	Model & Statistics	Australia	China	Hong Kong	India	Indonesia	Japan
2001.01.18 - 2011.02.28	DJ	0.799	2.935	2.374	2.941	2.226	2.102
	RW	1.125	2.976	2.731	3.055	2.391	2.671
	CW	5.146**	0.378	1.695*	0.800	1.333+	3.720**
2001.01.18 - 2007.07.31	DJ	0.391	2.174	1.171	2.074	1.671	1.704
	RW	0.505	2.164	1.346	2.170	1.765	1.887
	CW	1.756*	-0.015	2.008*	0.350	0.608	1.321+
2007.08.01 - 2011.02.28	DJ	1.566	4.368	4.639	4.572	3.272	2.849
	RW	2.293	4.504	5.339	4.722	3.569	4.146
	CW	4.875**	0.630	1.402+	0.885	1.255	3.522**
Forecasting Period	Model & Statistics	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand
2001.01.18 - 2011.02.28	DJ	2.489	0.799	1.981	1.622	2.090	2.214
	RW	2.749	0.858	2.300	1.776	2.316	2.302
	CW	1.646*	1.051	1.602+	1.555+	1.906*	0.502
2001.01.18 - 2007.07.31	DJ	2.282	0.717	1.535	1.099	1.888	1.987
	RW	2.508	0.760	1.664	1.193	2.043	2.041
	CW	1.286*	0.314	0.543	0.683	0.832	0.166
2007.08.01 - 2011.02.28	DJ	2.879	0.953	2.819	2.604	2.470	2.641
	RW	3.201	1.044	3.496	2.871	2.828	2.794
	CW	1.154	1.544+	1.528+	1.650*	2.153*	0.776

Notes: 1) R indicates the rolling sample technique. 2) DJ uses Dow Jones stock returns as a forecasting variable. 3) RW implies the random work without drift. 4) CW implies the Clark and West test statistic. 5) +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively, based on one sided tests.

In equation (5), $\hat{\sigma}_{RW}^2$ and $\hat{\sigma}_{DJ}^2$ are the sample MSPE of RW and DJ models. SE indicates an autocorrelation consistent standard error. $\hat{\sigma}_{RW}^2 - \hat{\sigma}_{RW}^2 - (\hat{\sigma}_{DJ}^2 - adj)$ implies the sample average of $\hat{f}_{T+\tau} = (y_{T+\tau} - \hat{y}_{RWT,\, T+\tau})^2 - [(y_{T+\tau} - \hat{y}_{DJT,\, T+\tau})^2 - (\hat{y}_{RWT,\, T+\tau} - \hat{y}_{DJT,\, T+\tau})^2]$.

$\hat{y}_{jT,\, T+\tau}$ is the τ-step ahead forecast at period T from model j. $\hat{f}_{T+\tau}$ is regressed on a constant and the resulting t-statistic for a zero coefficient is used as a test for equal MSPE.

Table 5 contains Clark and West (2007) test statistics (CW) on the difference of MSPE between DJ and RW. In DJ, the MSPE obtained by using the rolling sample technique is reported in table 5. According to the test results, DJ has a smaller MSPE than RW in all countries, and the difference of MSPE between these two models is statistically significant at the conventional level for Australia, Hong Kong, Indonesia, Japan, Korea, Philippines, Singapore, and Taiwan. $^{+}$, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively, based on one sided tests.

In order to investigate the possibility that global financial crisis engenders the difference in the forecasting results, the whole out-of-sample forecasting period is divided by two periods. In August 2007, the subprime financial crisis erupted in the U.S. and the Fed began to respond by lowering the federal funds rate from 5.25% to 4.75% on September 2007 (Mishkin, 2010). Therefore, August 2007 is considered as the starting period of the global financial crisis in the paper. Table 5 shows MSPE and Clark and West (2007) test statistics (CW) for the pre-crisis period from January 18, 2001 to July 31, 2007. The rolling sample technique has a better predictive power than RW in all countries but China. Table 5 also shows MSPE and CW for the post-crisis period from August 1, 2007 to February 28, 2011. The results are not the same as those for the pre-crisis period. In all cases, DJ has smaller MSPE than RW and the difference of MSPE between the two models becomes bigger.

6. COMPARISON OF DIRECTIONAL ACCURACY

In the former section, the size of the forecast error is compared. In light of the investors, it is more critical to be aware of the profitability of the forecast than the size of the forecast error. Yet, the profitability of the forecast appears to have a direct connection with directional accuracy of the forecast rather than MSPE and therefore, we need to measure the direction of the stock return change using forecasting models. In this section, Henriksson and Merton (1981) tests are carried out in order to investigate whether the direction of the change derived from DJ (1) has statistically significant accuracy.

$P_1(P_2)$ is assumed to be the conditional probability that both actual and forecasting values are less (greater) than 0. The Henriksson and Merton test examines the possibility that the sum of the conditional probabilities of a correct forecast, $P_1 + P_2$, is greater than 1 using the following test statistic.

$$V = \frac{n_1 - E(n_1)}{\sigma(n_1)}, \tag{6}$$

$$E(n_1) = \frac{n N_1}{N}, \tag{7}$$

$$\sigma^2(n_1) = \frac{n_1 N_1 (N - N_1)(N - n)}{N^2 (N - 1)}, \tag{8}$$

where n_1 represents the number of observations that both actual and forecasting values are less than 0 and n represents the number of observations that forecasting values are less than 0 without relation to the sign of the actual values. V follows the hypergeometric distribution approximated by the normal distribution. In equations (7) and (8), N_1 implies the number of observations in which the actual values are less than 0 and N is the total number of observations.

The test results for DJ (R) are reported in table 6. $P_1 + P_2$ is greater than 1 in all countries for the whole sample period.[15] It is statistically significant at the 1% level in all countries but China. P_1 and P_2 are greater than 0.5, respectively, in all stock markets for the whole period. It implies that DJ has the predictability for both the rise and the fall of stock returns. In all

[15] As table 3 shows, DJ has the best out-of-sample performance among local, regional, and global variables. In table 4, all models except RW basically include DJ. But their performance is always not better than that of DJ.

Table 6 Henriksson and Merton Test for DJ (*R*)

Forecasting Period	P_1, P_2 & Statistics	Australia	China	Hong Kong	India	Indonesia	Japan
2001.01.18 - 2011.02.28	P_1	0.669	0.502	0.607	0.546	0.569	0.598
	P_2	0.673	0.519	0.623	0.558	0.577	0.622
	P_1+P_2	1.342	1.033	1.230	1.103	1.146	1.220
	V	20.936**	1.466	14.576**	7.046**	9.847**	13.785**
2001.01.18 - 2007.07.31	P_1	0.658	0.475	0.615	0.538	0.556	0.579
	P_2	0.654	0.488	0.627	0.544	0.562	0.595
	P_1+P_2	1.313	0.963.	1.242	1.082	1.118	1.174
	V	15.770**	-2.111*	12.302**	4.638**	6.514**	9.006**
2007.08.01 - 2011.02.28	P_1	0.687	0.553	0.593	0.559	0.594	0.635
	P_2	0.709	0.577	0.617	0.585	0.605	0.672
	P_1+P_2	1.396	1.130	1.209	1.144	1.199	1.307
	V	13.846**	5.050**	7.856**	5.533**	7.709**	10.880**
Period	P_1, P_2 & Statistics	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand
2001.01.18 - 2011.02.28	P_1	0.576	0.597	0.598	0.596	0.576	0.568
	P_2	0.578	0.606	0.623	0.607	0.593	0.586
	P_1+P_2	1.154	1.203	1.221	1.203	1.169	1.154
	V	10.450**	13.158**	13.795**	13.101**	10.939**	10.052**
2001.01.18 - 2007.07.31	P_1	0.573	0.576	0.573	0.596	0.567	0.562
	P_2	0.570	0.581	0.594	0.600	0.584	0.576
	P_1+P_2	1.143	1.157	1.167	1.197	1.151	1.137
	V	7.941**	8.437**	8.581**	10.382**	7.909**	7.275**
2007.08.01 - 2011.02.28	P_1	0.580	0.635	0.645	0.594	0.593	0.581
	P_2	0.596	0.653	0.677	0.620	0.609	0.605
	P_1+P_2	1.176	1.288	1.322	1.214	1.202	1.186
	V	6.836**	10.574**	11.455**	8.004**	7.716**	7.058**

Notes: 1) R indicates the rolling sample technique. 2) P_1 implies the conditional probability that $y_{T+k} < 0$ and $\hat{y}_{T+k} < 0$. 3) P_2 implies the conditional probability that $y_{T+k} > 0$ and $\hat{y}_{T+k} > 0$. 4) V indicates the Henriksson-Merton test statistic. 5) * and ** denote significance at the 5% and 1% levels, respectively, based on two sided tests.

cases, P_2 is greater than P_1. That is, the predictive ability of DJ is reduced when stock returns decrease rather than increase. Among the twelve countries, Australia has the biggest value of $P_1 + P_2$, whereas China has the smallest value of $P_1 + P_2$.

Table 6 also shows the forecasting results of directional accuracy for the pre-crisis period from January 18, 2001 to July 31, 2007. In all countries except China, $P_1 + P_2$ is greater than 1, which is statistically significant at the 1% level. P_1 and P_2 are greater than 0.5 in all countries but China, whereas P_1 and P_2 are less than 0.5 in China. $P_1 + P_2$ is the biggest in Australia.

Table 6 finally reports the forecasting results for the post-crisis period from August 1, 2007 to February 28, 2011. In all countries, $P_1 + P_2$ is greater than 1 and statistically significant at the 1% level. $P_1 + P_2$ is increased, compared to those in the pre-crisis period. The exception is Hong Kong. P_1 as well as P_2 is greater than 0.5, for all countries including China. These results are different from those for the pre-crisis period. $P_1 + P_2$ is biggest in Australia and smallest in China.

7. CONCLUSIONS

This paper investigates which variables among domestic, regional, and global variables are helpful in order to predict the daily stock returns among twelve Asian countries since the 2000s using the out-of-sample forecasting analysis. First, through a comparison of the size of forecast error using MSPE, the study examines the possibility that the forecasting models with these variables as forecasting variables are superior to the random walk without drift or with drift. The Henriksson and Merton test is also carried out for a comparison of each forecasting model's directional accuracy.

In out-of-sample forecasting analysis, each country's own stock returns and exchange rates are used as domestic variables. Regional variables include the weighted Asian stock price indices which are derived from multiplying each stock price by its dollar GDP weight and stock market capitalization weight in twelve Asian countries, respectively. The Dow Jones stock prices, ￥/$ exchange rates, and federal funds rates are considered as global financial variables.

The comparison results of out-of-sample MSPE show that global, regional, and local variables, in an orderly manner, are useful to predict the twelve Asian countries' stock returns. Particularly, among forecasting models, the model using the Dow Jones Index as a forecasting variable has the smallest MSPE. According to the test results of Clark and West (2007), the difference of MSPE between this model and the random walk with no drift is statistically significant at least at the 10% significant level for eight countries over the whole sample period. However, the models using domestic variables as forecasting variables are inferior to the random walk without drift in most countries. The random walk without drift is generally superior to the random walk with drift. Similarly, DJ without an intercept outperforms DJ with an intercept in all cases.

The Henriksson and Merton test results for DJ, which has the smallest MSPE, suggest that the Dow Jones Index is also very valuable in predicting the direction of the stock return change. In all countries except China, the null hypothesis that $P_1 + P_2$ is greater than 1 is statistically significant at the 1% level for the whole period. For all countries except China, both P_1 and P_2 are greater than 0.5. This implies that the Dow Jones Index is useful in predicting both the rise and fall of stock returns. Among the twelve countries, $P_1 + P_2$ is the biggest in Australia, whereas it is the smallest in China.

APPENDIX

All Ordinaries (All Ordinaries Index, AOI)) is the oldest stock index in Australia. The market capitalization of the companies contained in the AOI amounts to over 95% of the value of all stocks included on the Australian

Securities Exchange. Shanghai Composite is an index of all stocks that are traded at the Shanghai Stock Exchange. It includes A shares and B shares. Hang Seng is a market capitalization-weighted stock market index in Hong Kong. It is the main indicator of the overall market performance in Hong Kong. Bombay Sensitive 30 (BSE 30 or SENSEX) is a market capitalization-weighted stock market index of 30 large companies which are representative of various industrial sectors of the Indian economy. The market capitalization of BSE 30 amounts to 50% of that of BSE. Jakarta Composite (JSX Composite) is an index of all stocks on the Indonesia Stock Exchange. Nikkei 205 is a stock market index for the Tokyo Stock Exchange. It is the most widely quoted average of Japanese equities. Seoul Composite (KOSPI) is the index of all common stocks traded on the Stock Market Division of the Korea Exchange. KLSE Composite (Kuala Lumpur Composite Index) is a capitalization-weighted stock market index. It includes the 30 largest companies listed on the Malaysian main market. PSE Composite (PSEi) is the main stock index of the Philippine Stock Exchange. It is one of the indicators on the general state of the Philippine economy. Straits Times (Straits times Index, STI) is a market capitalization-weighted stock market index of the top 30 companies listed on the Singapore Exchange. STI is considered as the benchmark index for the Singapore stock market. Taiwan Weighted (Taiwan Capitalization Weighted Stock Index) is a stock market index of companies traded on the Taiwan Stock Exchange. It covers all of the listed stocks except for some stocks such as preferred or newly listed stocks. SET (Stock Exchange of Thailand Index) is an index of all common stocks on the main board of the Stock Exchange of Thailand. It is a market capitalization-weighted price index and a composite economic indicator. Dow Jones 30 Industrial is a stock market index of the 30 large, publicly owned companies which are based in the US. In spite of some criticism, it is still the most cited and most widely recognized stock market index.

Table A1 Correlation Coefficients of Stock Returns

	DJ_{t-1}	AUS_t	CHI_t	HON_t	IND_t	INA_t	JAP_t	KOR_t	MAL_t	PHI_t	SIN_t	TAI_t	THA_t
DJ_{t-1}	1.000	0.518	0.102	0.381	0.183	0.242	0.430	0.317	0.254	0.333	0.319	0.278	0.206
AUS_t		1.000	0.207	0.599	0.385	0.403	0.583	0.511	0.384	0.400	0.560	0.424	0.156
CHI_t			1.000	0.308	0.171	0.155	0.186	0.148	0.152	0.121	0.209	0.157	0.153
HON_t				1.000	0.461	0.437	0.569	0.574	0.398	0.346	0.692	0.447	0.464
IND_t					1.000	0.362	0.326	0.365	0.271	0.239	0.485	0.295	0.339
INA_t						1.000	0.358	0.370	0.376	0.343	0.479	0.334	0.381
JAP_t							1.000	0.552	0.349	0.343	0.519	0.426	0.344
KOR_t								1.000	0.343	0.315	0.566	0.494	0.402
MAL_t									1.000	0.304	0.459	0.309	0.378
PHI_t										1.000	0.330	0.289	0.300
SIN_t											1.000	0.437	0.499
TAI_t												1.000	0.313
THA_t													1.000

Note: 1) IND and INA are abbreviations for India and Indonesia, respectively.

Table A2 Out-of-Sample MSPE Using the Univariate Regression without an Intercept (T=1000)

		Domestic Variables		Regional Variables		Global Variables		RW	
		SR	EX	$GDP	SMC	DJ	YEN	FFR	
Australia	R	1.247	1.228$^{4)}$	1.227$^{3)}$	1.230^{5}	0.859$^{1)}$	1.214$^{2)}$	1.246	1.240
	A	1.242	1.226$^{3)}$	1.231$^{4)}$	1.231^{5}	0.885$^{1)}$	1.219$^{2)}$	1.241	1.240
China	R	3.192	3.880	3.182$^{5)}$	3.186	3.128$^{1)}$	3.174$^{3)}$	3.170$^{2)}$	3.182$^{4)}$
	A	3.185	3.218	3.177$^{3)}$	3.180^{4}	3.139$^{1)}$	3.188	3.169$^{2)}$	3.182$^{5)}$
Hong Kong	R	2.864	2.841$^{3)}$	2.865	2.869	2.464$^{1)}$	2.814$^{2)}$	2.843$^{4)}$	2.850$^{5)}$
	A	2.857	2.823$^{3)}$	2.857	2.856	2.445$^{1)}$	2.821$^{2)}$	2.838$^{4)}$	2.850$^{5)}$
India	R	3.220	3.211$^{4)}$	3.222	3.224	3.058$^{1)}$	3.200$^{2)}$	3.216$^{5)}$	3.203$^{3)}$
	A	3.204$^{4)}$	3.213	3.206$^{5)}$	3.207	3.068$^{1)}$	3.197$^{2)}$	3.232	3.203$^{3)}$
Indonesia	R	2.406$^{4)}$	2.437	2.392$^{2)}$	2.405$^{3)}$	2.218$^{1)}$	2.425$^{5)}$	2.433	2.427
	A	2.395$^{4)}$	2.424	2.376$^{2)}$	2.386$^{3)}$	2.228$^{1)}$	2.419$^{5)}$	2.425	2.427
Japan	R	2.571	2.407$^{2)}$	2.507$^{4)}$	2.515$^{5)}$	1.887$^{1)}$	2.425$^{3)}$	2.558	2.560
	A	2.564	2.449$^{2)}$	2.517$^{4)}$	2.518$^{5)}$	1.945$^{1)}$	2.449$^{3)}$	2.551	2.560
Korea	R	2.358	2.342$^{5)}$	2.339$^{2)}$	2.342$^{4)}$	2.095$^{1)}$	2.340$^{3)}$	2.354	2.350
	A	2.352	2.335	2.335$^{3)}$	2.336$^{4)}$	2.107$^{1)}$	2.320$^{2)}$	2.347$^{5)}$	2.350
Malaysia	R	0.713$^{4)}$	0.717	0.700$^{2)}$	0.705$^{3)}$	0.653$^{1)}$	0.717$^{5)}$	0.722	0.719
	A	0.707$^{4)}$	0.726	0.700$^{2)}$	0.703$^{3)}$	0.643$^{1)}$	0.715$^{5)}$	0.719	0.719
Philippines	R	2.411	2.369$^{5)}$	2.273$^{2)}$	2.291$^{3)}$	1.970$^{1)}$	2.326$^{4)}$	2.378	2.375
	A	2.387	2.381$^{5)}$	2.284$^{2)}$	2.291$^{3)}$	2.019$^{1)}$	2.344$^{4)}$	2.372$^{5)}$	2.375
Singapore	R	1.720	1.712$^{3)}$	1.722	1.722^{5}	1.539$^{1)}$	1.706$^{2)}$	1.719	1.715$^{4)}$
	A	1,719	1.716$^{4)}$	1.716$^{5)}$	1.717	1.527$^{1)}$	1.703$^{2)}$	1.712$^{4)}$	1.715$^{3)}$
Taiwan	R	2.004	1.994$^{5)}$	1.955$^{2)}$	1.965$^{3)}$	1.768$^{1)}$	1.982$^{4)}$	2.002	2.001
	A	2.001	1.983$^{5)}$	1.948$^{2)}$	1.956$^{3)}$	1.771$^{1)}$	1.981$^{4)}$	1.997	2.001
Thailand	R	2.255	2.203$^{2)}$	2.207$^{4)}$	2.213$^{5)}$	2.102$^{1)}$	2.199	2.216	2.205$^{3)}$
	A	2.212	2.195$^{2)}$	2.203$^{3)}$	2.205$^{5)}$	2.092$^{1)}$	2.205$^{4)}$	2.208	2.205

Notes: 1) SR, ER, DJ, YEN, and FFR use local stock returns, local exchange rate changes, Dow Jones stock returns, ¥/$ changes, and federal funds rate changes as a forecasting variable, respectively. 2) $GDP and SMC use Asian weighted stock returns obtained from dollar GDP and stock market capitalization weights as a forecasting variable, respectively. 3) RW implies the random work without drift. 4) R and A indicate the rolling and adding of sample techniques, respectively. 5) Numbers in the upper-right corner of MSPE show the rank of models.

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