G-3 and BRICK Stock Markets: Co-integration and Its Forecasting Ability

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ABSTRACT

This paper questions the widely held belief that stock markets of emerging countries are largely dependent on movements of developed markets. Are the emerging and the developed markets indeed tied together? If so, does the co-movement help us better predict returns on the emerging market equities in the short- and the long-term? To answer these questions, this paper first conducts co-integration tests for each pair of nine stock indices: the U.S., the U.K., Japan, Hong Kong, Brazil, Russia, India, China, and Korea. As a next step, this paper constructs real-time forecasting models by imposing the co-integration information and recursively forecasts stock returns of each BRICK (Brazil, Russia, India, China, and Korea) market with various investment horizons. The forecasting ability of the co-integration based model is assessed based on out-of-sample mean square prediction errors and success ratios of correctly predicting signs of the returns. Empirical results suggest that the emerging and the developed markets are not as strongly tied to each other as many investors have believed. Imposing the co-integration term on the forecasting model does not significantly improve forecasting accuracy but does improve the success ratio.

KEYWORDS: Emerging markets; Co-integration; Real time forecasting; Out-of-sample mean squared prediction error; Directional accuracy; Portfolio strategy

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1. INTRODUCTION

Global investors tend to look at emerging countries as being economically and financially dependent on developed countries. Due to their smaller size, financial dependence, and sometimes great reliance on commodity exports, the demand for which is highly correlated with the developed countries' business cycles, emerging markets (EM) have been very sensitive to price fluctuations of the developed markets (DM), while the reverse has not always been true. In short, the EM-DM relationship has been a one-way street.

As the EMs' share in the global economy has been growing, this one-way interaction has been evolving since the early 2000s (Markus, 2011). The EM economies has been growing significantly faster than their DM peers. According to the OECD's projection in 2010, the EMs will account for nearly 60% of combined GDP of the U.S., Japan, and Germany by 2015, and 60% of global output by 2030. According to Markus (2011), China, for instance, has already overtaken Japan as the world's second biggest economy when it recorded \$5.8 trillion of GDP at the end of 2010. A remarkable rebound of the EM equity markets amidst the meltdown of other DM equities in the post-crisis period has fueled further the debate on whether the EMs have decoupled from the DM.

The major EM and DM stock indices in global market and corresponding countries are listed in Table 1, and their performance since January 2000 is plotted in Figure 1. The EM indices have been definitely outperforming the DM indices. Especially, the performance of Brazil and Russia relative to their EM peers is remarkable. In Table 2, the two EM countries yielded highest nominal returns of 318% and 1,087%, respectively. By contrast, the DM stock indices have been almost stagnant and even yielded negative returns over the given period. As the divergence between the EM and the DM has become increasingly obvious in the recent post-crisis era, global investors are intensifying their focus on EM equities to seek the higher returns that they cannot expect in the DM. As seen in Table 2, however, the higher returns are accompanied by higher standard deviation. The Russian market, which yields nominal returns as high as 1087%, also involves the highest standard deviation of 11 as well as the highest kurtosis of 1.18. On average, the standard deviation of the returns on the five EM stock indices is 8.5, which is 3.5 higher than that on the four DM stock indices.

In order to successfully manage such high volatilities yet pursue high returns in the EM equities, investors often try forecasting future returns in the EMs by computing their correlations with other DMs. Figure 2 shows the real-time correlation of each pair of the nine stock indices since January 2000. Returns on Brazilian and Russian equities have relatively high correlations with those on other markets, while China shows the least exposure to external markets. It is also noteworthy that the correlation of returns across all markets has sharply increased since the global financial crisis of 2008. Investors might infer from Figure 2 how consistently the returns on a given pair of stock indices move together over time, but the correlation itself has substantial limitations as a tool for forecasting such asset returns. It can be helpful for forecasting short-term returns, but its day-by-day fluctuations contain no information about the long-term co-movement between the stock prices (Alexander, 2002). Hence, the correlation-based investment strategy requires frequent portfolio rebalancing.

A statistical method that might overcome such limitations is the co-integration approach. One fundamental difference between the co-integration and the correlation approaches is that the former refers to co-movements of two asset prices while the latter refers to those of asset returns. For example, if two stock prices are said to be highly correlated, one would likely go up on the day that its counterpart goes up, and vice versa. However, if the two stock prices are said to be co-integrated, the two prices are tied together by a common stochastic trend so that each of the two might fluctuate in the short-run but eventually move in the same direction in the long-run. As a result, a co-integration based portfolio diversification strategy requires less frequent rebalancing and may prove useful for long-term investment.

The purpose of this paper is to examine the two issues above and answer the following questions. Are the emerging and the developed stock markets tied together over the long-run? In other words, are the stock market indices co-integrated? If so, does this co-integration relationship help us predict returns on the emerging market equities more accurately? In Section 2, I describe the data and statistical methodologies employed in this paper. In Section 3.1., I conduct a test for co-integration relationships between each pair of the nine stock indices listed in Table 1. In that section, I provide not only a statistical interpretation of the test result, but also an economic interpretation of the co-integration relationships for each pair. Unlike the previous literature, I go beyond merely reporting the co-integration test results. I construct a univariate real-time recursive forecasting model of the returns on each emerging stock index based on the co-integration relationship between their stock prices. I assess the model's forecasting ability using the statistical tests suggested in Clark and West (2006) and Pesaran and Timmermann

(2009). In Section 3.2, based on results of these two tests, I recommend the best forecasting models for each EM stock market.

2. DATA AND METHODOLOGY

2.1. Data

The stock indices examined in this paper are listed in Table 1. There are total nine indices: four developed markets (the U.S., the U.K., Japan, and Hong Kong) and five emerging markets (Brazil, Russia, India, China, and South Korea). Historical data of the stock indices are obtained from FactSet, a financial data research system, and they are monthly closing prices in local currencies. A computational program mainly used for statistical tests in this paper is MATLAB.

One consideration when designing statistical tests is that the five emerging stock markets have relatively short histories compared to the DMs, and even their launching dates vary one another. As noted in Table 1, for instance, the Korean stock market launched in 1985 is the oldest one out of the five EMs, and the Russian market is the latest one whose index data are publicly available since September 1995. Due to this timing difference, this paper considers two types of sample periods for each pair of the nine stock indices when conducting the statistical tests. For a given pair, the first sample period, denoted as *T=1*, begins from the opening date of a more recently launched stock index to March 2011, and the second sample period, denoted as *T=2,* spans January 2000 to March 2011. For instance, *T=1* for a pair of Brazil and Russia indicates a sample period from September 1995 to March 2011.

2.2. Co-integration Test

The concept of co-integration rests on the work of Engle and Granger (1987). By definition, a series with no deterministic component, which has a stationary, invertible, ARMA representation after differencing d times, is said to be integrated of order d, denoted $y_t \sim I(d)$ (Engle and Granger, 1987). The vector y_t is said to be co-integrated of order 0 if the levels of y_{1t} and y_{2t} are *I(1)*, and if the linear combination of the two is *I(0)* with a co-integrating vector α such that

$$z_t = c' y_t = [c_1 \; c_2] \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = c_1 y_{1t} + c_2 y_{2t} \sim I(0) \qquad (1)$$

The term $c' y_t$ can be interpreted as a long-run equilibrium relationship under co-integration, which implies that deviations from the equilibrium are stationary even though the series itself is not (Engle and Granger, 1987). In other words, even though the two stock prices can wander arbitrarily in the short-run, they are tied together in the long-run and share a common stochastic trend that leads to a long-run equilibrium.

Let y_{1t} be the natural logarithm of a stock price where *t = 1,2,…T* and *T* is the sample size. Let y_{2t} be the log price of another stock. The co-integrating vector c is $[c_1\ c_2] = [1 \quad -1]$., which is the same as the one assumed in previous studies (Christoffersen and Diebold, 1998). Asset pricing models, which assume a simple and known co-integrating vector to be $[1 \quad -1]$, imply stable deviations between the two stock market indices. Although the assumption of a known co-integrating vector certainly involves a loss of generality, it has been used in a variety of empirical studies. Imposing the co-integration vector $[1 \quad -1]$, the equation (1) becomes

$$z_t = [1 \quad -1]\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = y_{1t} - y_{2t} \sim I(0) \qquad (2)$$

A widely used statistical method to test for co-integration of known form is the Augmented Dickey Fuller (ADF) test proposed in Dickey and Fuller (1979). The null hypothesis of the ADF test is that z_t in (2) is a unit root process. For the alternative hypothesis, two cases are considered. The first case, denoted as case 2 in Hamilton (1994), postulates a random walk with a mean under H_0:

$$z_t = \alpha + z_{t-1} + u_t \qquad (3)$$

and a model with a mean under H_1:

$$z_t = \alpha + \beta z_{t-1} + u_t \qquad (4)$$

The second case, denoted as case 4, postulates the random walk (3) under H_0 and a model with both a mean and a time trend under H_1:

$$z_t = \alpha + \rho t + \beta z_{t-1} + u_t \quad (5)$$

where u_t may be serially correlated over time with bounded fourth moment. The encompassing regression model z_t can be written equivalently as an AR(p) model of the form:

$$z_t = \alpha + \sum_{i=1}^{p} \beta_i z_{t-i} + \varepsilon_t = \alpha + \beta z_{t-1} + \sum_{i=1}^{p-1} d_i \Delta z_{t-i} + \varepsilon_t \qquad (6)$$

where we focused on case 2 for expository purpose. By subtracting z_{t-1} on both sides, equation (6) can also be re-written as:

$$\Delta z_t = \alpha + \delta z_{t-1} + \sum_{i=1}^{k} d_i \Delta z_{t-i} + \varepsilon_t, \ \ where\ \delta = \beta - 1 \qquad (7)$$

The ADF test evaluates H_0: $\delta = 0$ against H_1: $\delta < 0$, which implies $\beta < 1$. We rule out $\beta > 1$ because the time series z_t in (6) will be explosive when $\beta > 1$. To reject the null under the ADF test is to conclude that z_t is a stationary process and that the two stock prices are co-integrated. This paper considers both case 2 and case 4 for each pair of the nine stock indices, given that some pairs have apparent trends in z_t, but some are not.

The optimal lag length k in the ADF model (7) is determined by the sequential two-sided t-test suggested in Ng and Perron (1995), among others. Ng-Perron t-test starts with k_{max} from a set of possible values $\{0,1,\dots,k_{max}\}$, where k_{max} is selected a priori. I set k_{max}=12 considering that the stock indices are monthly data. If the t-test implies that the coefficient of the last lag, k_{max}, is significantly different from zero, then we select the optimal lag length $k = k_{max}$. Otherwise, k_{max} is reduced by one, and we apply the same OLS t-test on the coefficient of the new last lag, $k_{max} - 1$. This procedure is repeated until one coefficient is statistically significant, or $k=0$.

Once the lag order k is selected by the sequential t-test, we impose that lag order and compute a test statistics for δ in (7) by applying OLS. Asymptotic critical values for the ADF t-statistics are not reliable for this paper given its finite small sample size. One alternative to this problem is to bootstrap the finite sample critical values and to build an approximation of the distribution of the test statistics under the null hypothesis of no co-integration. Under the null in (7), we know that $\delta = 0$. In creating the bootstrap data-generating process (DGP), we impose this null hypothesis:

$$z_t{}^* = \hat{\alpha} + z^*{}_{t-1} + \sum_{i=1}^{k} \widehat{d_\iota} \Delta z^*{}_{t-i} + \varepsilon_t{}^* \qquad (8)$$

where $\varepsilon_t{}^*$ is a identically and independently distributed (i.i.d.) Gaussian white noise. We generate $r = 1, \dots, 2{,}000$ replications of $\{z_t{}^*\}_{t=k}^{T}$ in (8) and fit the unrestricted ADF model (7) to each bootstrap data set $\{z_t{}^*\}_{t=k}^{T}$. For the case 4, the bootstrapped DGP is defined as:

$$z_t{}^* = \alpha + \rho t + z^*{}_{t-1} + \sum_{i=1}^{k} d_i \Delta z^*{}_{t-i} + \varepsilon_t{}^* \qquad (9)$$

and we proceed analogously. We compute the percentiles of this finite-sample distribution of $t_{\hat{k}^*}^{r}$ to determine the bootstrapped critical value for $t_{\hat{\rho}}$. In this paper, $t_{\hat{\rho}}$ is chosen at the 90% confidence level under a two-sided test.

2.3. Real-time Out-of-sample Forecasting

In this section, I propose a real-time forecasting model for each emerging market's stock return that exploits the possible existence of a co-integration relationship. Even if a pair of stock indices is not found to be co-integrated, it is still worth trying to forecast returns in this manner. The fact that we fail to reject the null in the ADF test does not necessarily mean that the two stocks are not co-integrated. We have to consider possibility that the co-integrating vector $[1 \quad -1]$ is incorrect, or that the power of the test may be low. In these cases, it may still be useful to impose the co-integrating vector $[1 \quad -1]$ on our forecasting given the bias-variance tradeoff.

Rationales for the co-integration variable in a long-horizon forecasting are discussed in Christoffersen and Diebold (1998). Christoffersen and Diebold (1998) showed that imposing co-integration is not actually helpful for long horizon but helpful for short-horizon forecasting. Building on this insight, I propose to predict returns on EM stock indices based on z_t. Let $r_{y1,t+h|t}$ be h-month ahead forecasted returns on the stock index y_{1t} in (2). The proposed forecasting model is:

$$r_{y1,t+h|t} = \mu + \theta z_t + \varepsilon_t \qquad (10)$$

where $z_t = y_{1t} - y_{2t}$ and $h = 1, 3, 6, 12$ month horizons. This model is formally similar to the long-horizon regression model in Mark (1995) and Kilian (1999). Given that I consider a total of the nine stock markets, one can construct eight different models to forecast returns on an EM stock index. I compare the forecasting ability of the co-integration based (CB) forecasting model in (10) to that of a random walk. We consider two benchmark models: a random walk with drift (11) and a random walk without drift (12).

$$r_{y1,t+h|t} = \mu + \varepsilon_t \qquad (11)$$

$$r_{y1,t+h|t} = \varepsilon_t \qquad (12)$$

The first benchmark model allows for a trend, whereas the second does not. For a given data set available up to time t, we recursively estimate the coefficients, $\hat{\mu}$ and $\hat{\theta}$ in (10), and forecast cumulative returns $y_{1t+h} - y_{1t}$. This is equivalent to simulating how a real-world investor would have forecasted returns at the end of every month with stock price data available at that point.

To evaluate the performance of out-of-sample forecasts, we divide a given sample $\{r_{y1,t+h|t}\}_{t=1}^{T-h}$ into two sub-periods. Let the initial estimation period be $t = 1,2,\dots,t^*$, and the forecasting evaluation period be $t = t^*,\dots,T-h$. We first fit model (10) using the estimation sample and compute h-months return prediction at the forecast origin t^*. Then, we advance the forecast origin by one month and repeat computing h-months forward returns by fitting the new estimation sample until the forecast origin reaches $T-h$. The forecast evaluation period spans July 2004 to February 2011. The corresponding evaluation sample size is 80.

2.4. Tests of Equal MSPE and of Directional Accuracy

When evaluating the performance of the simulated out-of-sample forecasts of stock returns, we consider two criteria: the CB model's MPSE and the number of times that the signs of the forecasted returns correspond to those of actual returns. The first criterion, forecasting accuracy, is assessed using the Clark-West (2006) test. The second criterion, the success ratio of predicting the stock market directions, is assessed using the directional accuracy test proposed in Pesaran and Timmermann (2009).

Forecasting Accuracy: Clark-West Test (2006)

The out-of-sample CB forecasting model in (10) is compared to the random walk models in (11) and (12). These two models are nested. In the case of comparing two nested models, we can employ the Clark-West test with asymptotic critical values.

Clark and West (2006) proposed a statistical test to see whether two forecasting models have equal forecast accuracy, which is particular to comparing two nested models with estimated parameters. Let the random walk in (11) and (12) be a null and the CB model in (10) be an alternative. Expectations conditional on current and past z_t's and past e_t's, denoted as E_{t-1}, are assumed as: $E_{t-1}e_t \equiv E(e_t|z_t, e_{t-1}, z_{t-1}, e_{t-2}, \ldots)$ (Clark and West, 2006). Under both the null and the alternative, e_t is a zero mean martingale difference: $E_{t-1}e_t = 0$. Since e_t has conditional mean zero, it is serially uncorrelated, yet it might be conditionally heteroskedastic (Clark and West, 2006).

The Clark-West test evaluates the null model against the alternative via comparison of out-of-sample mean squared prediction errors (MSPEs). Consider two sets of out-of-sample forecasts, $\{\hat{r}^{rw}{}_{y1,t+h|t}\}$ from the random walk in (11) or (12) and $\{\hat{r}^{reg}{}_{y1,t+h|t}\}$ from the CB model in (10). Given the number of predictions used in computing the MSPEs, denoted as N_0, the respective MSPEs of the null and the alternative are:

$$\widehat{\delta_1}^2 = N_0^{-1} \sum_{t=T-N+h}^{T} \left(r_{y1,t+h} - \hat{r}^{rw}{}_{y1,t+h|t}\right)^2 \quad (13)$$

$$\widehat{\delta_2}^2 = N_0^{-1} \sum_{t=T-N+h}^{T} \left(r_{y1,t+h} - \hat{r}^{reg}{}_{y1,t+h|t}\right)^2 \quad (14)$$

Clark and West (2006) showed that the mean loss differential, $\bar{d} = (\widehat{\delta_1}^2 - \widehat{\delta_2}^2)$, is not normally distributed but skewed to the right in a case of comparing two nested models, and suggests an alternative approach that evaluates the null by examining $\bar{d} = (\widehat{\delta_1}^2 - \widehat{\delta_2}^2_{adj})$, where $\widehat{\delta_2}^2_{adj}$ is defined as:

$$\widehat{\delta_2}^2_{\ adj} \equiv \widehat{\delta_2}^2 - N_0^{-1} \sum_{t=T-N+h}^{T} \left(\hat{r}^{reg}{}_{y1,t+h|t}\right)^2 \quad (15)$$

Under the null, the MSPE-adjusted test statistic $\bar{d} = \left(\widehat{\delta_1}^2 - \widehat{\delta_2}^2_{adj}\right) = 0$, which implies that the two nested models have equal forecasting accuracy. Under the alternative, $\bar{d} > 0$, the prediction error of the CB model is less than that of the random walk. Clark and West (2006) demonstrated that the t-statistic is approximately normally distributed. If p-values of the MSPE-adjusted t-statistics are less than 0.10, the null hypothesis of equal forecasting accuracy can be rejected at the 90% confidence level. In other words, we conclude that the CB model has lower MSPE than the random walk model.

Directional Accuracy: Pesaran-Timmermann Test (2009)

Because the loss function for the Clark-West test produces squared terms of the forecast error, it does not tell us whether the forecasted returns have the same signs as actual returns. We, therefore, also consider the success ratio which is the percentage of the number of times that the signs of the forecasted returns correspond to those of actual returns. The benchmark random walk amounts to a success ratio of 50% like tossing a coin. Therefore, any success ratio which is significantly greater than 50% indicates the CB model's directional accuracy.

Pesaran and Timmermann (1992) first proposed a distribution-free procedure for testing directional accuracy. This nonparametric statistical framework can be applied as follows. Let $P_x = Pr\left(\hat{r}^{reg}{}_{y1,t+h|t} > 0\right)$ and $P_y = Pr\left(r_{y1,t+h} > 0\right)$, where $\hat{r}^{reg}{}_{y1,t+h|t}$ and $r_{y1,t+h}$ are predicted and actual returns in (14). Also let the success ratio be $\hat{P} = \frac{1}{T}\sum_{i=1}^{n} Z_i$, where Z_i is an indicator function that the predicted and the actual returns have equal signs. Under an assumption that $\hat{r}^{reg}{}_{y1,t+h|t}$ and $r_{y1,t+h}$ are independently distributed, $n\hat{P}$ has a binomial distribution with mean nP^*, where $P^* = P_y P_x + \left(1 - P_y\right)(1 - P_x)$ (Pesaran and Timmermann, 1992). If the CB forecasts turn out to have the same sign as the actual returns, the resulting percentage $\hat{P}$ should exceed the mean of the binomial distribution P^*, which stands for no forecasting accuracy under the null. This earliest version of the directional accuracy test, however, assumes the absence of serial correlation in the signs of the actual and predicted returns, which is unrealistic. In order to address this issue, Pesaran and Timmermann (2009) suggested an alternative framework of testing serial dependence of categorical variables. Consider a regression model:

$$\theta' x_{2,t} = c + \gamma' x_{1,t} + u_t, \;\; where \;\; u_t = \varphi u_{t-1} + \varepsilon_t \;\; and \; |\varphi| < 1 \quad (16)$$

$x_{1,t}$ and $x_{2,t}$ are multi-categorical variables, and u_t are serially dependent while ε_t are serially independent. In the presence of the serial dependencies, the model (16) is a form of dynamically augmented reduced rank regression with canonical correlation coefficients between the categorical variables. Specifically let:

$$x_{1,t} \equiv \begin{cases} 1, \; sign(\hat{r}^{reg}{}_{y1,t+h|t}) > 0 \\ 0, \; sign(\hat{r}^{reg}{}_{y1,t+h|t}) < 0 \end{cases}, \; x_{2,t} \equiv \begin{cases} 1, \; sign(r_{y1,t+h}) > 0 \\ 0, \; sign(r_{y1,t+h}) < 0 \end{cases}$$

When there is only one categorical explanatory variable, as in this paper, the augmented reduced rank regression reduces to testing the significance of a slope coefficient in a univariate time series model of $x_{2,t}$ on $x_{1,t}$ (Pesaran and Timmermann, 2009). Under the null, $\gamma' = 0$, and under the alternative, $\gamma' > 0$. Pesaran and Timmermann (2009) showed that standard test statistics, $\hat{t}_\gamma$, for (16) are asymptotically normally distributed. If the estimated coefficient, $\widehat{\gamma'}$, is found to be statistically significant at the 90% confidence level based on asymptotic critical values, we conclude that the CB forecasting model has directional accuracy.

3. EMPIRICAL RESULT AND INTERPRETATION

3.1. Co-integration

Co-integration between the EM and the DM

As seen in Table 4, among the five EMs, Brazil is the only emerging market that is co-integrated with all of the four DMs: U.S., U.K., Japan, and Hong Kong. Its co-integration with each DM stock index is statistically significant for both case 2 and case 4, based on the sample period from January 1993 to March 2011. The Brazil-DM co-integration relationship implies short- and long-term strategies, both of which might be useful to global investors who want to diversify their portfolios. The co-integration relationship implies that, for a given pair of stocks, if one stock price temporarily falls below the long-term co-movement trend, it would ultimately move upward to restore the trend and trace its counterpart. Taking advantage of this co-integration property, the short-term strategy is as follows. When a pair of the Brazil stock index and one DM index (S&P 500, for example) appears to divert from their historical co-movement trend, the investors take a short position for one of the stocks, which moves above the trend, and a long position for the other stock, which falls below the trend. Profits can be earned as the two stocks begin converging to their long-run equilibrium. In terms of the long-run strategy, if the investors expect the G-3 stock markets to be bullish in near future, they can consider increasing portfolio weights on Brazil because the two markets share the same long-run movements and are expected to yield high returns eventually.

Based on the sample period from January 2000 to March 2011, it can be found that the Korean stocks have been co-integrated with those of the U.S. and Hong Kong; and the India stocks have with Japan's. By contrast, Russia and China equities show no co-integration relationships with all of the four DM equities. Then, why do those three markets—Brazil, Korea, and India—share long-term price movements with the G-3 markets while the Chinese and the Russian do not? Here are some possible explanations.

Brazil and the developed economies

The first factor that might explain the Brazil-DM relationship is the major composite of the Brazil stock index, which is considerably related to business cycles of the developed economies. The Brazil stock market consists of two sectors in large. As of March 2011, according to FactSet, more than 40% of its total market capitalization is in energy and non-energy mineral sectors, and the rest of the composites are in domestic consumption-driven sectors such as commercial banking and consumer discretionary. Particularly, two largest companies in the energy and mining sectors—Petrobras and Vale—account for 24% ($366 billion) and 17% ($267 billion) of the total Brazil equity market value, respectively. Petrobras and Vale are ranked in the global top ten oil and mining companies, and most of their productions, including oil, iron ore, and cooper, are shipped to the U.S., EU, and China. According to CIA (2010), the U.S., EU, China, Japan, and India are ranked as the top five oil consumers in the world, consisting of 49% of total global oil consumption per day. It is notable that the five regions are all found to be co-integrated with the Brazil stock index in Table 4. Because the commodity prices are substantially dependent on business cycles of these major economies, share prices of Brazilian oil and mining giants must have been subjected to stock performances of the five countries. This commodity export-import relationship might be one of the reasons for the broad co-integration relationships of Brazil with the DMs as well as with other EM peers.

Second, Brazil provides the most accessibility and investment opportunities to foreigners among the EM peers. As seen in Table 5, equity ownership and business operations by foreigners in Brazil are evaluated as very flexible. The Brazilian government has set very open legal framework on foreign investors and has formed friendlier environments for FDI than the governments of other emerging countries. Mining, construction, retail, transportation, financial services, and real estate—these industries are the major ones that foreign investors are particularly interested in when seeking for investment opportunities in emerging countries. We can see in Table 5 that all of these major industries in Brazil have removed almost all restrictions on FDI. Such open policies for FDI and foreign investment inflow may have played an important role in creating the co-integration relationship between Brazil and the DMs.

Korea and the U.S.

As for the co-integration of Korea with U.S., great dependence on the Korean economy on foreign trade can be a reasonable explanation. South Korea, with a long history of export-driven economic growth since the 1960s, has shown the largest dependence on exports and imports among G20 nations. According to Principal Global Indicators (PGI) jointly issued by IMF and OECD in 2010, Korea's exports and imports together accounted for 84% to its GDP, while for other G20 countries, it was generally around 50% to 60% to GDP. Traditionally, about 80% of the Korean exports have comprised of electronic machinery (30%), chemicals (20%), and automobiles (10%), and today these sectors are the top three composites of the Korean stock index by their market values. As of March 2011, according to FactSet, the three major sectors account for 40% of total Korean equity market, as represented by Samsung Electronics ($155 billion of market capitalization) and Hyundai Motors Group ($99 billion.) Earnings of these export-driven companies are subject to key currency exchange rate (USD/KRW) and household consumption in the developed regions. Considering that the largest trade partner for Korea has been the U.S. for the last several decades, the Korean stock market's co-integration with the U.S. market must be no coincidence.

In addition to the substantial reliance on the foreign trades, relatively open market environments toward foreign investors must drive the Korean stock market to be more integrated with the U.S. as well as Hong Kong, which is the main trading window of Asia to western investors. The OECD Index in Table 5 clearly suggests that the Korean market, like Brazil's, is very open to foreign investors compared to China, India, and Russia. According to the Bank of Korea, foreign ownership in the Korean stock market has been generally between 30% and 40% for the last ten years, and this figure is the highest among other Asian peers including Taiwan (30%), Singapore (23%), and Thailand (20%). The more the foreign investors hold Korean equities, the more the Korean market is sensitive to movements of the DMs. Korea's such high vulnerability to external factors would explain its co-integration relations with U.S. and Hong Kong.

India and Japan

Another interesting result to take a look at in Table 3 is that the Indian stock market appears to be co-integrated with the Japanese market in the sample period from January 2000 to March 2011. Presumably, this is due to an industry value chain linked from India's iron ore production to Japan's steel and auto makers. For decades since World War II, India has played a significant role in the growth of Japan's steel and auto industries, as more than 75% of total iron ore exported from India landed in Japanese steel mills. Japan does not have either iron ore or coal and is fully dependent on imports of these natural resources from India. According to statistics released by WTO, mining and fuel products are the second largest export from India, accounting for about 26% of the total exports as of 2010. This fact might imply that the Indian stock market has co-moved with stock prices of Japanese steel and automobile manufacturers, both of which have showed rapid growth since the 1980s. Japan today is the second largest steel producer after China. Nippon Steel, which is expected to acquire Sumitomo Metals in 2012, will be ranked as the world largest steel maker, supplying about 7% of global production, according to World Steel Association. Japan is also the largest auto maker in the world as its auto companies, including Toyota, Honda, and Nissan, have maintained about 26% of global market share for the last decade. This long-term industrial linkage between India and Japan might have shaped the strong tie between the two equity markets.

A geographical factor should be considered along with FDI. As seen in Table 3, India shows no co-integration with other western markets. Geographically, India is located closer to Japan than to the western regions, while Brazil is located just below North Africa and beside the European continent. Due to the favorable location, the two major western investors might have preferred Brazil to the emerging Asia including India. According to statistics released from the

World Bank, the total FDI accumulated from 1990 to 2000 was \$137.5 billion in Brazil; by contrast, it barely reached \$19 billion in India. This geographical factor might support why the Indian stock market is co-integrated with the Asian big economy, Japan, while the Brazilian market is tied to the major western economies.

Disintegration of Russia and China

In contrast to Brazil, Korea, and India, Russia and China are found to be not co-integrated with the DMs. Why do these two emerging countries show such different characteristics from Brazil, Korea, and India? Interestingly, Russia, like Brazil, is one of the largest energy producers in the world. According to CIA (2010), Russia and U.S. are the world's largest natural gas suppliers accounting for 18% of global production each in 2010. Moreover, the Russian equity market composition is more heavily weighted on the energy sector than Brazil's. As of March 2011, according to FactSet, 51% of the total Russian market capitalization is attributable to natural gas and mining companies, including Gazprom (16%), Lukoil (15%), and Novatek (8%). It is reasonable to question why Brazil's stock market has exposure to the developed economies while Russia's does not.

Russia's relatively short history of capitalism and privatization might be one major reason for its disintegration from the long-term co-movement with the DMs. After the collapse of communist and socialist regimes in the early 1990s, Central and Eastern European (CEE) economies began transforming into capitalism by establishing legal framework for private property and capital markets. Among them, Russia has definitely displayed the most outstanding economic growth and rapid capitalization in its stock exchange market, boosted by its abundant amount of natural resources. Many previous literatures attempted to investigate linkages between the Russian and global markets. Its overall evidence, while mixed, was that the Russian market is segmented from other western markets and even from its regional CEE neighbors, reaching to the same conclusion as this paper's. Lucey and Voronkova (2008) concluded that even in a case where a structural break after the repercussion of the Russian currency and debt crisis of 1998 is considered in their co-integration analysis, the Russian market still remains disintegrated with the developed economies over the sample period from 1994 to 2004. The dynamic conditional correlation (DCC) analysis in Lucey and Voronkova (2008), however, suggests that conditional bivariate correlations between the Russian and the developed markets have gradually increased in the post-crisis period, even though their correlation is very weak. It seems that the transition of Russian market from the CEE region to broader global markets is still on the way, which explains why the co-integration relationship representing a long-term co-movement has not yet been established.

Another probable reason for Russia's disintegration from the DMs is its market's closedness to foreign investors. This explanation is applicable to the Chinese stock market as well. In Table 5, it is easily noticeable that the Russian and Chinese markets provide the least accessibility to foreign investors, compared to other three EM peers and OECD countries. Specifically, equity ownership and business operations in both markets are very restrictive to foreigners. The most striking numbers in the Table 5 are the ones that indicate the extent of the closedness of Russian mining industry, 0.94, compared to that of Brazil, 0.03. FDI in the mining sector is almost locked up to foreigners in Russia, while in Brazil, it is almost open to all regardless of nationality. In fact, most of the natural gas companies in Russia, including Gazprom and Novatek together consisting more than 20% of the Russian stock market value, are owned by the Russian government. This excessive restriction imposed by the state on the private market explains why the Brazilian market can be co-moved with the DMs but the Russian market cannot, even though both stock markets are represented by major energy producers.

In addition to Russia, China is still regarded as a closed market to foreign equity investors. Shanghai Stock Exchange (SSE) Composite Index is the most commonly used indicator to reflect the Chinese stock performance. One of the distinctive features of the SSE Composite is that its constituents are traded in two separate markets: A-shares and B-shares. Ownership of the A-shares, denominated in Yuan, had been restricted to Chinese citizens, while B-shares, denominated in USD, were allowed to be traded only by foreigners. Moreover, convertibility of Yuan into USD dollars was not, and is still not, flexible in mainland China. These restrictions by the Chinese government, which aimed at suppressing capital outflow from its mainland and preventing foreign control of domestic firms, resulted in segmentation of the A-share and the B-share markets. The A-share market became very popular among the mainland investors, recording resilient growth in terms of its trading volume and market capitalization. By contrast, the B-share market rarely received attention from foreign investors. According to China Securities and Futures Statistical Yearbook of 2007, the Shanghai stock market reached total capitalization as large as 43% of China's GDP at the end of 2006, but most of the market value was the A-shares'. The B-share market accounted for only 1.4% of the total SSE capitalization. Companies listed in B-share were 7.6% of all listed companies in SSE, and those which issued both A- and B-shares were 6.5% at most. Foreign investors who wanted to invest in Chinese companies bought H-shares instead of the B-shares, the third type of Chinese stocks listed in the Hong Kong Exchange Market. Yet, only 20% of the total 143 H-shares were being traded in the A-share market. These statistics all imply that the three segments of the Chinese stock market cannot co-move because their constituents are rarely overlapped. Considering this distinctive feature of the Chinese market, it is no surprise that China shows no co-integration with the DMs and even with its neighbor Hong Kong. Belatedly in 2002, the Chinese government allowed foreigners to buy the A-shares but limited to those who acquired Qualified Foreign Institutional Investor (QFII) licenses from the government itself.

Moreover, as of March 2011, according to FactSet, 20% of total market capitalization in SSE consists of commercial banks which most of them were formerly run by the Chinese government and are still under the umbrella of the state. For instance, Industrial and Commercial Bank of China (ICBC) with $220 billion of market value is today's second largest stock in the SSE. In the 2000s, many state-owned regional banks including the ICBC, China Construction Bank, and Bank of China, went public. Their share prices after the IPOs drove outperformance of the Shanghai stock index compared to other Asian indices. Earnings of the Chinese banks have been driven by domestic credit growth in their mainland, not by performance of other western economies, and partially by the state policies. No one can deny the great presence of the Chinese economy in the global economy, yet the segmented structure and the big portion of the banking sector in the Shanghai market may have prevented Chinese equities from forming a co-integration relationship with the DM and Asian EM equities.

Co-integration among the EMs

The Brazilian stock index again shows broad co-integration relationships with other EM peers. As seen in Table 4, based on the sample period since January 1993, the ADF test of Case 2 finds that Brazil has been co-integrated with India, China, and Korea. If the beginning date of the sample period changes from January 1993 to January 2000, we cannot find sufficient evidence for the Brazil-EM co-integration relationship. This does not necessarily reduce reliability of the co-integration result found from the sample period of January 1993, because the co-integration test is more reliable when its sample period gets longer. In addition to the three Brazil-EM pairs, Korea and India show a co-integration relationship based on the sample period from January 2000 under the ADF test of Case 4. Russia again turns out to be disintegrated with other EM peers.

Then, what would be a reasonable explanation for the EM-EM co-integration relationships? One major reason might be a pattern of capital flows across the DM and the EM. During a good time with optimistic investment sentiments, a massive amount of global capital flows into the EM asset markets and thereby boosts up stock prices on those markets. During a period of uncertainty, by contrast, global investors reduce their positions in assets invested abroad and increase the degree of home bias in their portfolios. For instance, in January 2011 after political unrest in Egypt broke out, investors, alarmed by the political risk of EM countries, withdrew a total of $5.4billion from EM equity funds during the first two weeks of February 2011. The average of weekly capital outflows from the EM funds recorded $5 billion in that month, which was the largest ever since 2001 (Panigirtzoglou, 2011). By sharp contrast, DM equity funds saw a massive inflow of $12 billion in the meantime. The divergence of the DM and the EM capital flows was also at its highest ever. This home-bias phenomenon by global investors, which usually occurs when the EM investment risks suddenly rise, would have been an underlying factor for the EM-EM co-integration relationships.

3.2. Forecasting Accuracy of the Co-integration Based (CB) Model

The CB model would be considered useful for investors if (1) its forecasting accuracy were statistically significant compared to a random walk's under the Clark-West test, and if (2) its directional accuracy were statistically significant under the Pesaran-Timmermann test. Even though the CB model fails to beat the benchmark random walk in terms of its forecasting accuracy, it might still convey helpful guidance for investors if it has statistically significant ability to predict the stock market direction.

Table 7 through Table 11 shows test results of the CB model's forecasting ability for Brazil, Russia, India, China, and Korea, respectively. The MSPE ratio of less than 1 implies that the CB model has less prediction squared error than the random walk. Success ratio is the percentage of the number of forecasted returns that have equal signs to actual return signs, out of the total 80 forecasts. Some p-values computed by using Pesaran-Timmermann test, denoted as

N/A, are the cases where all the CB model's forecasted returns have one sign, resulting in its variance of 0. The zero variance makes it impossible to calculate the test statistics for the Pesaran-Timmermann test, so we report their corresponding p-values as '*Not Available.*'

Figure 3 through Figure 7 are scatterplots which visualize the test results for each CB model. These scatterplots are to promote understanding of investors who want to see the statistical test results at a glance by each emerging country. The MSPE ratios are on the x-axis and the success ratios on the y-axis. Countries marked as 'X' are those with neither statistically significant forecasting accuracy nor directional accuracy when employed in the CB model. Some countries marked as '▲' have statistically significant forecasting accuracy only; some marked as '▼' have directional accuracy only.

The scatterplots display the CB forecasts' statistical significance as well as economic significance. The two red dotted lines on the scatterplots indicate MSPE ratios of 1 and success ratios of 50%. A CB model must be economically useful for investors who wish to forecast returns on each EM only if its MSPE ratio is less than 1 and the success ratio is greater than 50%. Hence, some CB models, which yield particularly high MSPE ratios or low success ratios, are excluded from plotting, regardless of their statistical significance.

Overall, none of the CB models has been found to satisfy the two qualifications of an optimal forecasting model. However, we can find some CB models for each of the five EM indices, which satisfy either the forecasting accuracy or the directional accuracy in short- and long-term horizons.

Brazil

As seen in Figure 3, the CB models paired with the U.S., China, or Korea can improve forecasting accuracy when predicting short-term returns on Brazil's stock index. In the 1-month and 3-month forecasting horizons, the three CB models are statistically significant under the Clark-West test and yield MSPE ratios of less than 1. If we consider directional accuracy at the same time, however, forecasting short-term returns on Brazil with the CB models would not be recommendable. None of the models is found to be statistically significant under the Pesaran-Timmermann test in the short-term horizons.

As for 12-month forward returns, the CB models paired with the U.S., U.K., Hong Kong, Russia, India, China, or Korea appear to outperform the random walk without drift. In Table 7, all of these seven CB models are statistically significant under the Clark-West test. However, U.K. and Hong Kong shall be excluded from our consideration at this point, because their MSPE ratios are greater than 1. The rest of the five CB models perform very well in the long-term horizon in contrast with the short-term horizons. It is notable that the five models have very high success ratios of predicting signs of the returns, all of which are around 70% or 80%. Unfortunately, however, statistical significance of these models' directional accuracy cannot be concluded at this point, because computing their test statistics for the Pesaran-Timmermann is impossible. Accordingly, as seen in Table 7, their p-values for that test are denoted as '*N/A*'. Yet, such high success ratios still involve economic significance for investors who wonder whether the Brazilian stocks will go up or down.

This result of the forecasting ability has some implications, in association with that of the co-integration relationships discussed in Section 3.1. Brazil is found to be the only country that shows long-term co-movements with all of the four DMs, China, India and Korea. The co-integration relationships, however, are not necessary and sufficient conditions for investors to forecast long-term returns on its stock prices. Japan, U.K., and Hong Kong—these three countries that are co-integrated with Brazil are not helpful when paired with Brazil in the CB models. By contrast, Russia has no co-integration relationship with Brazil but shows the best performance in forecasting long-term returns on the Brazilian stock index. The CB model paired with Russia yields the lowest MSPE ratio of 0.76 and the highest success ratio of 85%.

In summary, the best CB models to forecast the Brazilian stock market are as follows. For 1-month short-term returns, the model paired with the U.S. can improve forecasting errors compared to the benchmark random walk, but it is not expected to correctly predict the Brazilian market's directions. For 12-month long-term returns, the CB model paired with Russia is recommended, given its statistically significant forecasting accuracy and economically significant directional accuracy. The models paired with China, India, Korea, or the U.S. can be the second best options.

Russia

The test result for Russia in Figure 4 contrasts greatly with that for Brazil in Figure 3. The CB models forecasting returns on Russia yield statistically significant success ratios that are generally higher than those for Brazil. The CB models for Russia also result in lower MSPE ratios than those for Brazil, although statistically insignificant under the Clark-West test.

Overall, the CB model is found to be a useful guidance for future market directions in both short- and long-term forecasting horizons. As for 1-month forward returns on the Russian market, the CB model paired with either China or Korea is recommendable as its success ratios are 66% and 61%, respectively. The success ratios in the short-term horizon are improved further as the forecasting horizon gets longer. For 6-month forward returns, the CB model paired with Korea improves its success ratio from 61% to 70%, and for 12-month forward returns, the ratio reaches up to 78%. The U.S. also plays a role in the 6-month and 12-month forecasting horizons, as the CB model paired with the U.S. marks 54% and 61% of success ratios, respectively.

Implications from the CB models for Russia are along the same lines as those for Brazil. Even though Russia appears to have no co-integration relationships with the DMs and the EMs, the co-integrating vectors, paired with these markets, are statistically significant in forecasting the Russian market's directions in the near future.

India

As seen in Figure 5, the CB model paired with Japan shows outstanding performances in predicting stock market directions of India in both short- and long-term horizons. Its success ratios are 65% in 1-month and 63% in 3-month horizons, and are improved further in long-term forecasting horizons, as much as 69% in 6-month and 70% in 12-month period. Interestingly, this improvement has been found in the case of forecasting the Russian market's directions by using the co-movement with Korea's. However, we cannot expect the CB model paired with Japan to outperform the random walk in terms of forecasting accuracy.

In fact, none of the CB models shows improved forecasting errors compared to the random walk in the short-term horizons, but the one paired with China does show in the 12-month forecasting horizon. It is found to be statistically significant under the Clark-West test with the MSPE ratio of 0.88. The CB model paired with the U.S. is also statistically significant, but, given that its MSPE ratio is greater than 1, it cannot be considered as a good forecasting tool.

Overall, Japan is the best counterpart of the CB model when predicting the Indian market's directions in both short- and long-term horizons. Japan's considerable role in predicting the Indian market supports the co-integration relationship found between the two in Section 3.1. Despite having no co-integration relationship with India, China can be considered as the second option when investors expect less forecasting error in the 12-month horizon.

China

In Figure 6, none of the counterparts in the CB model for China is distinguished for its forecasting accuracy. All of the CB models are statistically insignificant under the Clark-West test in both short- and long-term horizons. As for market direction forecasting, however, two models are found to be statistically significant: the one paired with Korea in the 1-month horizon and the other paired with the U.S. in the 3-month and 12-month horizons. Despite its statistical significance, the CB model paired with Korea will not be helpful in the real world due to its success ratio of less than 50%. By contrast, the model paired with the U.S. shows success ratios of higher than 50%, which are 55% in the 3-month and 60% in the 12-month horizons.

In fact, the overall performance of the CB models for China is very striking to that for Russia, despite the fact that Russia and China are the only two countries that are found to have no co-integration relationships with other markets. Russia finds the U.S., Korea, and China as its efficient counterparts to be paired with in the CB model, but China finds only the U.S. Interestingly, the Chinese stock market is useful when predicting the Russian market's directions, but the reverse is not. It is also noticeable that success ratios of the CB models for Russia are generally higher than those for China. For instance, Russia's CB model paired with Korea yields as high as 78%, compared to China's CB model paired with the U.S., which ends up with 60% of the success ratio at best. These empirical findings confirm again that imposing the co-integrating vector in the CB model does not always result in better forecasting in the long-term horizon.

Korea

As seen in Figure 7, the Korean market's future directions are fairly well predicted by the CB model paired with the U.S. in the 1-month horizon, yet the model's success ratio is relatively low at 49%. When paired with Russia, however, the CB model performs much better, as its success ratios are 71% in the 3-month, 74% in the 6-month, and 78% in the 12-month forecasting horizons. An interesting point here is that even though the U.S. shows a co-integration relationship with Korea, Russia is actually a more efficient counterpart for the CB model for Korea in the long-term forecasting horizons. It is also notable that Russia and Korea are the most efficient counterparts to each other when predicting each stock market's future directions.

In terms of forecasting accuracy compared to the random walk, none of the CB models shows statistical significance in short-term forecasting horizons. Only for the 12-month horizon, the U.K. and Hong Kong show forecasting error improvements as their MSPE ratios are 0.79 and 0.85, respectively. Considering that the U.K. results in lower MSPE ratio than Hong Kong, the U.K. is actually a better counterpart for Korea than Hong Kong despite the co-integration relationship between Korea and Hong Kong.

Which CB model for China with directional accuracy has less forecasting errors over time?

What global investors are most interested in today is how to forecast returns on the Chinese market as accurately as possible. Unfortunately, however, none of the CB models for China is statistically significant under the Clark-West test. When paired with either the U.S. or Korea, the CB model will be some help for investors who want to know at least whether Chinese equities will yield positive or negative returns in the near future. If these investors want to select one with less forecasting error, which model of the two will be a better choice? The CB model paired with the U.S. or Korea? Both models are not rejected under the Clark-West test, meaning that their forecasting accuracy cannot beat the random walk for most of the time over the sample forecasting period. But can either of the two models sometimes outperform the benchmark in a particular period?

Figure 8 gives an answer to this question. Prediction squared errors from the two CB models are plotted over the real-time forecasting period from July 2004 to February 2011. As for 1-month forward returns, the two models do not outperform the random walk for most of the period. However, it is noticeable that the CB model paired with Korea does outperform in short-term horizons from January 2008 to January 2009, and so does the model paired with the U.S. in the long-term horizon.

Figure 8 implies two meaningful lessons. First, in the beginning of the global financial crisis in 2008, the Chinese stock market must have been better forecasted by its historical co-movements with other markets rather than by the random walk. This is presumably due to contagious effects of the global crisis across the countries. Second, despite the fact that the U.S. asset market was the origin of the global crisis in 2008, the EM peers, rather than the U.S., must have been chosen as a counterpart to be paired with in the CB model for China in the short-term horizons. As the U.S. stock market plummeted in August 2008, the emerging stock markets were hard hit all together by massive fund withdrawal led by western investors. For example, if a portfolio manager were to forecast a 3-month forward return on China in May 2008, he should have chosen Korea. As for 12-month ahead forecasting, it becomes a different story. The CB model paired with the U.S. does outperform the random walk as much as the model paired with Korea does in two periods. These periods can be characterized as the pre-crisis economic boom from early 2006 to mid-2007 and escalation of the global market crash from early 2008 to early 2009. For instance, if the portfolio manager had chosen the U.S. when forecasting 12-month forward returns on China in October 2007, he could have achieved both forecasting accuracy and directional accuracy.

Can we reduce errors of forecasted returns on Chinese stocks by averaging the CB forecasts?

After reviewing forecasting results for China, one might ask whether the average of the two forecasted returns from two CB models may be more accurate than those from any single CB model. For example, we might combine China-the U.S. and China-Korea pairs when forecasting returns on Chinese equities. As seen in Table 6, this alternative model is very promising given its low MSPE ratio of 0.7. The improvement in the averaged CB forecasts is plotted in Figure 9. The alternative model clearly beats the benchmark random walk over the period from early-2006 to mid-2009 in the 12-month horizon, in contrast with the short-term horizons. However, we encounter a trade-off if we select the averaged CB model. As seen in Table 6, we lose statistically significant ability to predict future market directions, which the single CB models previously had.

4. CONCLUSION

Based on the empirical findings in Section 3, this paper reaches three key considerations. First, it is by no means true to argue that stock price movements of the emerging markets are dependent on those of the developed markets and therefore share the same trends with the DMs. Some EMs are co-integrated with the DMs, but some are not. Among the five EMs sampled in this paper, Brazil is the only one that has co-integrated relationships with *all* four DMs. The other EMs that show long-term ties to specific DMs are Korea with both the U.S. and Hong Kong, and India with Japan. Surprisingly, China and Russia seem to be independent from co-movements with the DMs. These co-integration test results might be attributable to links of major industries between the EM and DM economies and their export-import relationships, or legal frameworks that prohibit or support foreign investors' equity ownership and FDI in the EMs. The co-integration among the EMs themselves is also noticeable. Brazil has the most exposure to not only the DMs but also other EM peers. By contrast, Russia seems to be independent even from its EM peers.

Second, imposing the co-integration in a forecasting model does not necessarily improve the model's forecasting ability, and sometimes a counterpart having no such relationship turns out to be actually useful in CB forecasting. This is probably because the thesis that the co-integration can improve forecasting ability in a long-term horizon might be wrong, or because, even if the thesis is right, the variances of the estimated parameters in the CB model are large so that its MSPEs are large as well. Overall, we cannot find an optimal forecasting model for any given pair of countries, which has both forecasting accuracy under the Clark-West test and directional accuracy under the Pesaran-Timmermann test. However, we can recommend some CB models with either of the two forecasting qualifications, and these models might be a considerable help to those who want to predict returns on each of the five EMs over various forecasting horizons.

Yet, the methodology employed in this paper has some limitations. One major caveat is that the CB forecasting model does not consider historical movements of CPI inflation rates and exchange rates. The CPI inflation rates in the EMs are generally higher than those in the DMs because they are largely affected by commodity prices such as oil, gas, and food. The exchange rates between USD and the EM currencies are also subject to high volatility. When making investment decisions, global investors understand that these two factors may affect the returns on their foreign investments. Stock returns discussed in this paper, however, are all nominal and in local currencies. If this paper had controlled for inflation and gain/loss on foreign currency transactions as two additional variables in the CB model, empirical results for the model's forecasting ability might have been different.

Another limitation of this CB model is that combinations of more than two countries are not considered when testing the integration relationships and constructing the CB model. Given the nine stock indices in total, each EM stock index can have $\sum_{i=1}^{8}\binom{8}{i} = 255$ possible combinations of its counterparts for the CB model. This paper considers 8 pairs for each stock index, which account for only 3% of all possible forecasting models. If we had extended the CB model paired with a single country into one with multiple countries, we might have been able to obtain more promising results. Moreover, the averaged CB model suggested as an alternative in Section 3.2. assumes that each counterpart has an equal weight of influence on one country's stock market that we want to forecast. However, in the real world, the weights must be different depending on particular relationships among the markets, such as value chains of certain industries or the volume of bilateral trade. Future research needs to be carried out to complement the two caveats of this paper.

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APPENDIX

Figure 1. Historical Price Movements of Major Stock Indices[1]

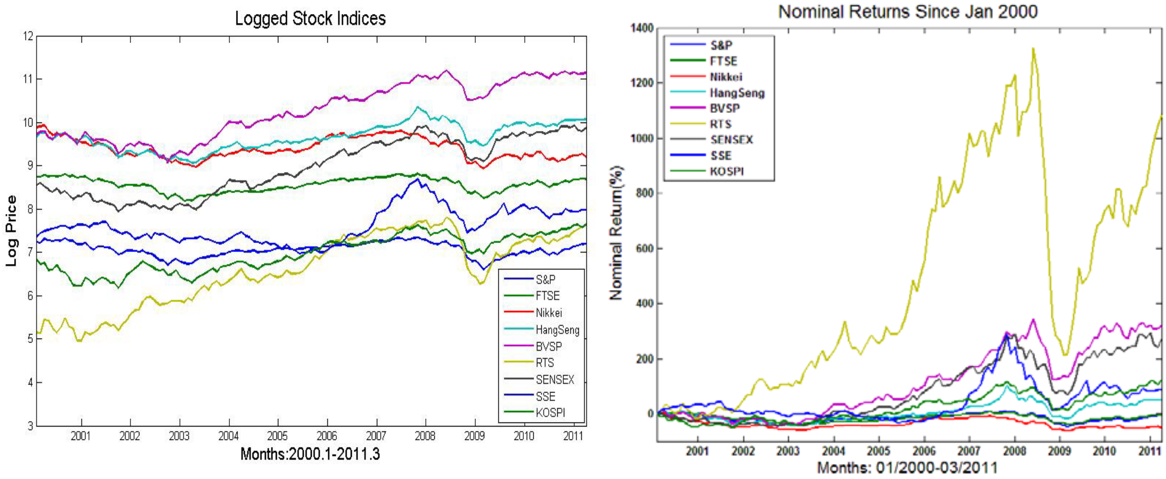
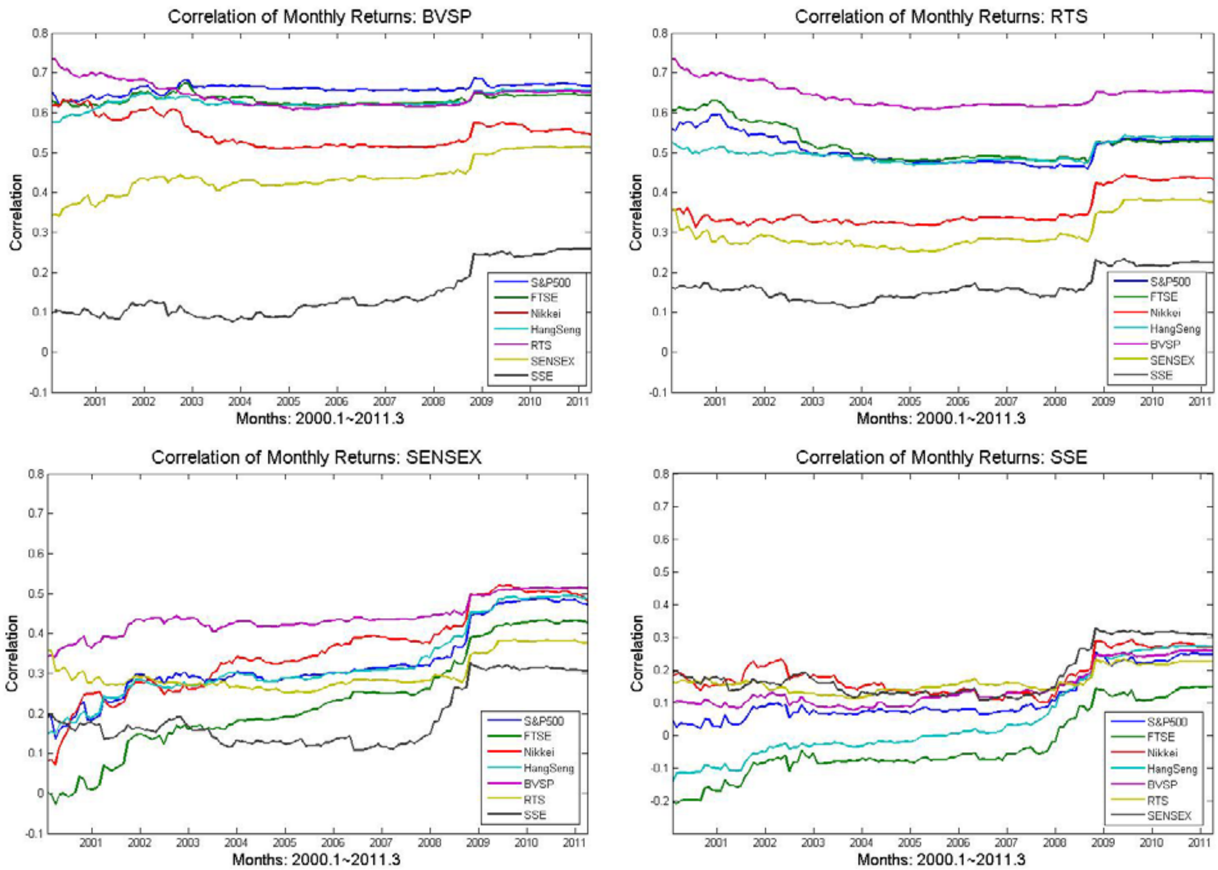


Figure 2. Correlations of Monthly Returns on EM indices



[1] Price movements of the nine stock indices are in natural logarithms, and their nominal returns are computed excluding dividend payouts since January 2000.

Figure 2. Correlations of Monthly Returns on EM indices (Cont'd)

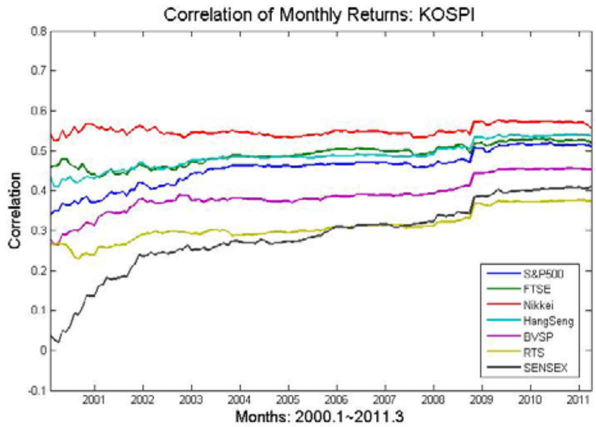


Figure 3. Forecasting diagnostics of a co-integration based model for Brazil

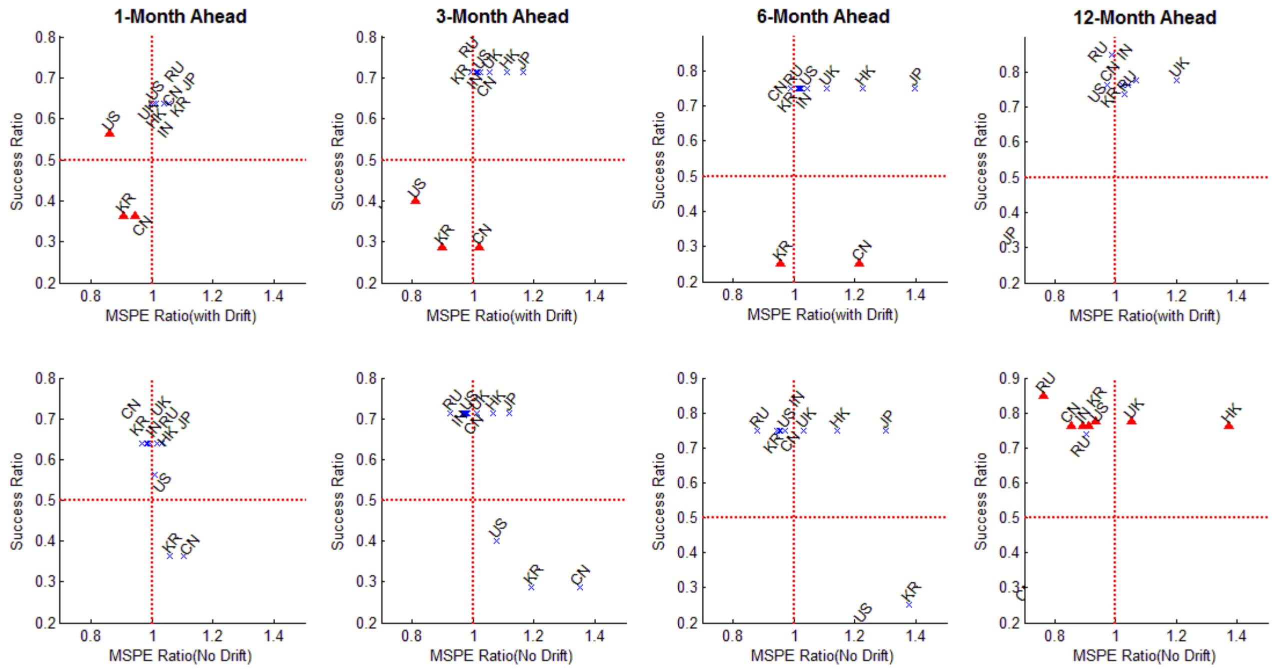


Figure 4. Forecasting diagnostics of a co-integration based model for Russia

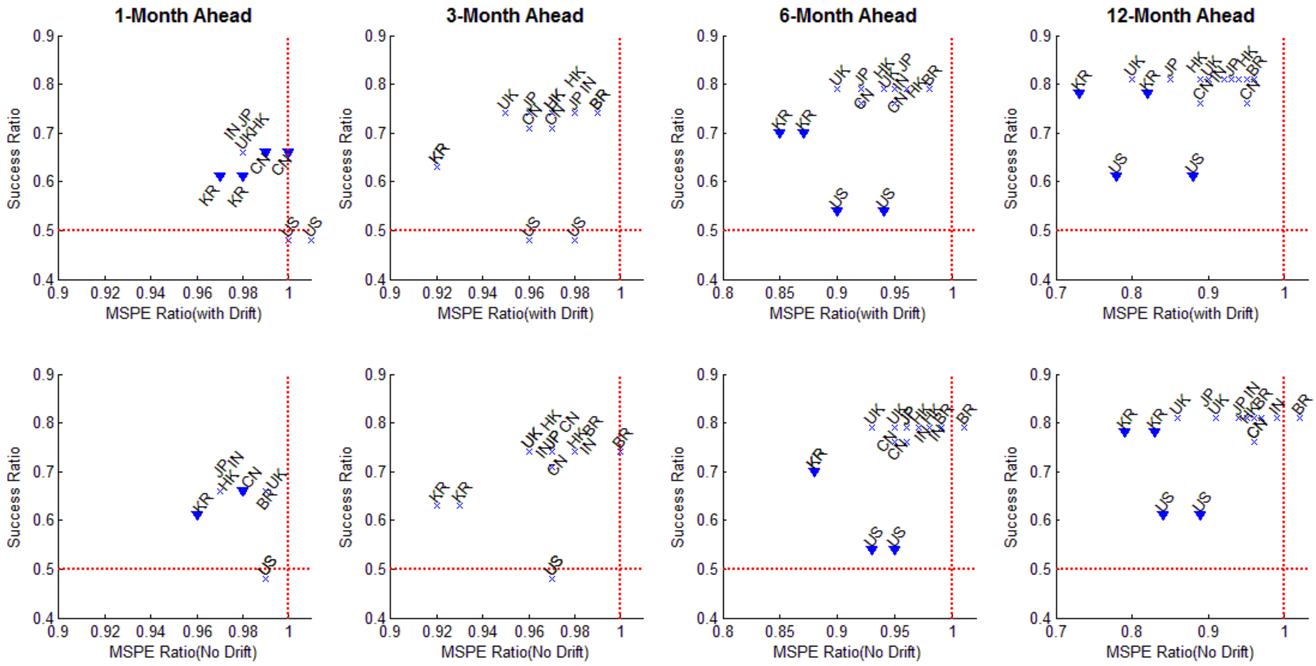


Figure 5. Forecasting diagnostics of a co-integration based model for India

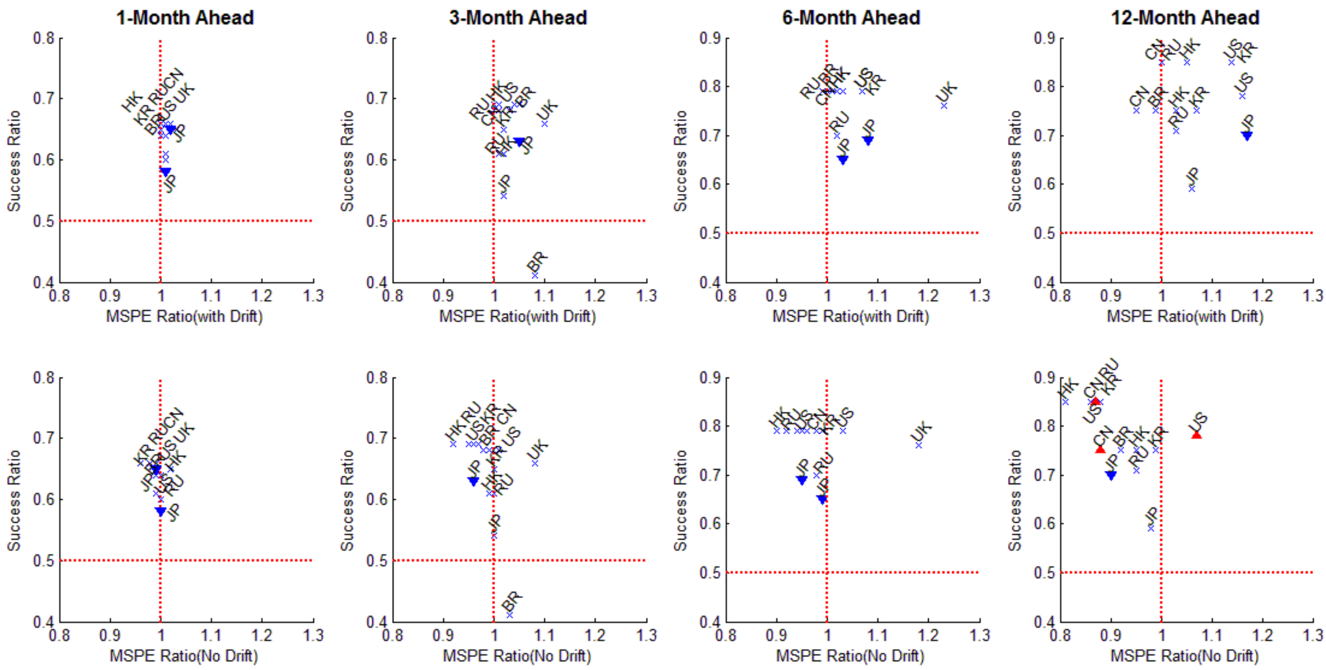


Figure 6. Forecasting diagnostics of a co-integration based model for China

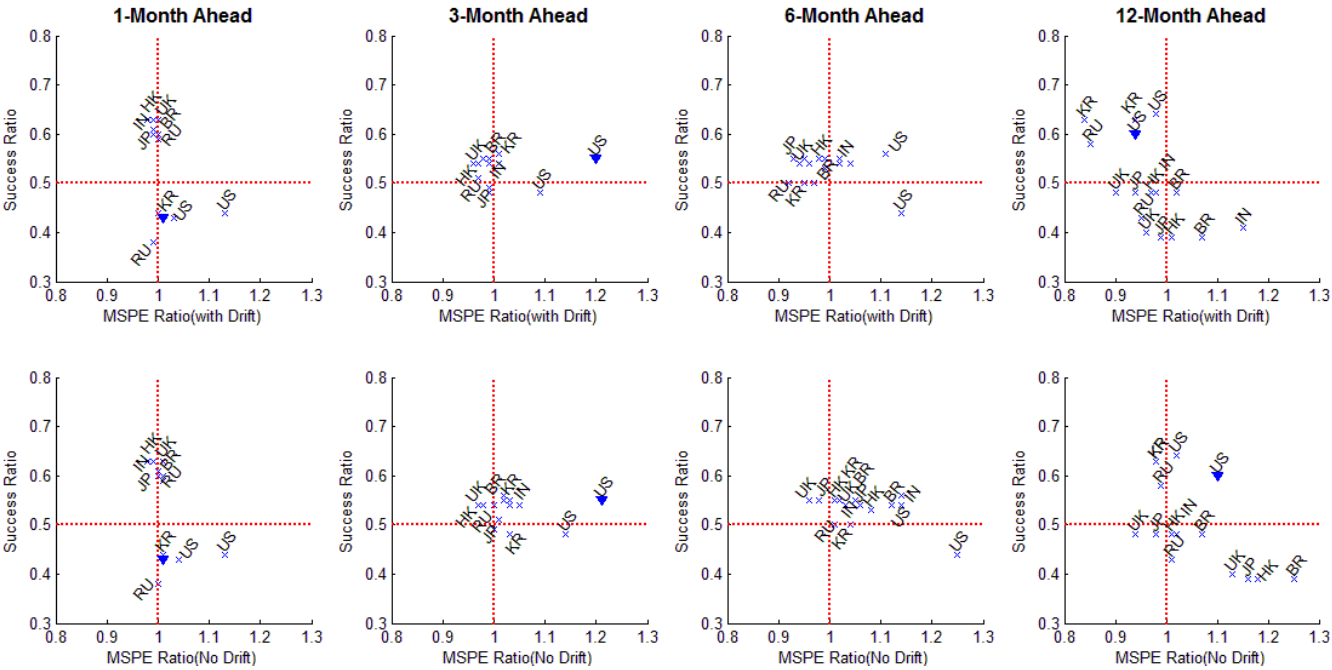


Figure 7. Forecasting diagnostics of a co-integration based model for Korea

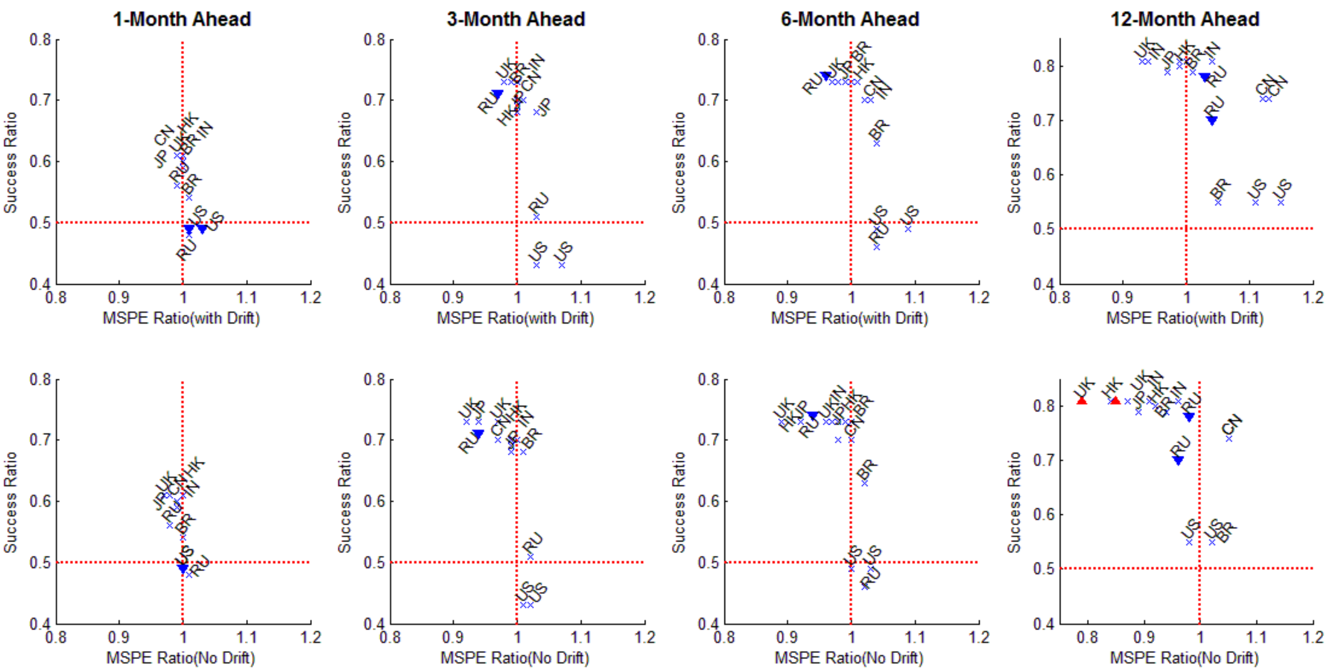


Figure 8. Prediction Squared Error of a CB model, paired with the U.S. vs. Korea, for China

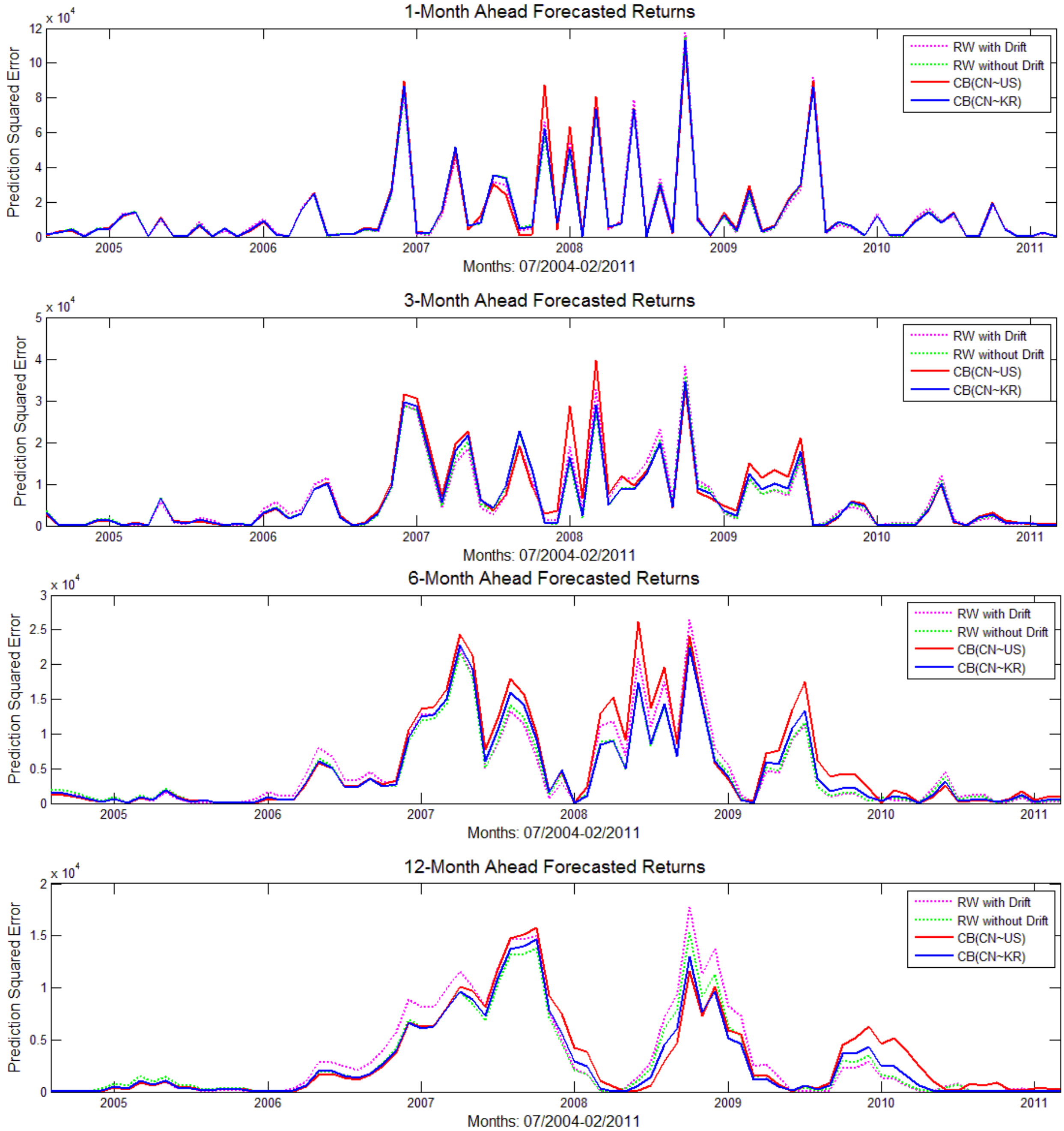


Figure 9. Prediction Squared Error of Averaged CB Forecasts for China

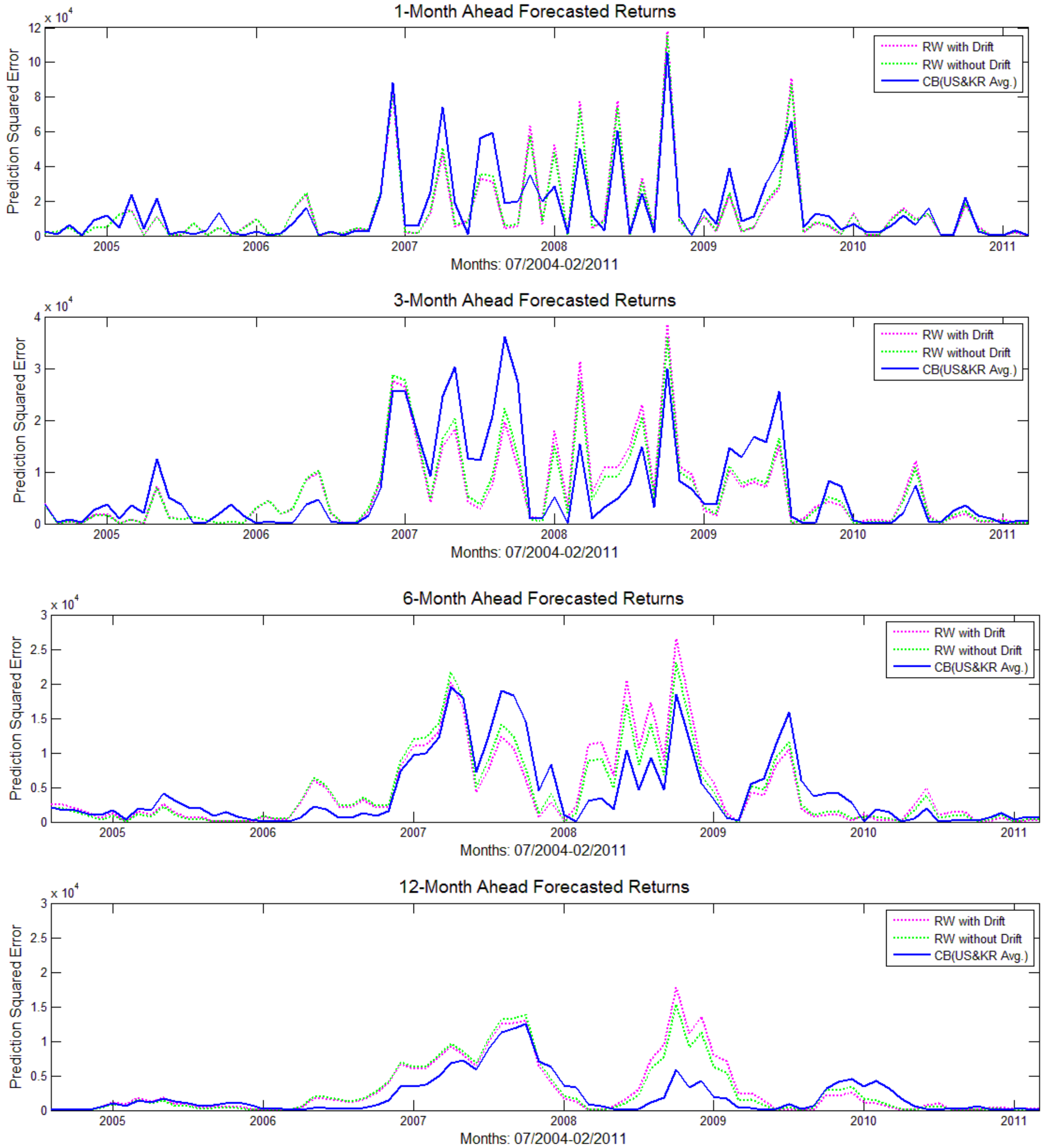


Table 1: Major Stock Indices

Market	Index Name	Country	Market Capitalization	Sample Period
Developed	S&P 500	U.S.	10,300	1986.1-2011.3
	FTSE U.K.	U.K.	2,882	1986.1-2011.3
	Nikkei 225	Japan	2,294	1986.1-2011.3
	Hang Seng	Hong Kong	1,252	1986.1 -2011.3
Emerging	IBovespa	Brazil	1,736	1993.1-2011.3
	RTS Standard	Russia	768	1996.9-2011.3
	BSE SENSEX	India	603	1988.1-2011.3
	Shanghai SE Composite	China	2,971	1992.5-2011.3
	KOSPI Composite	Korea	1,024	1986.1-2011.3

Notes: As of March 2011, the indices of the U.S., the U.K., Japan, and Hong Kong are incorporated in MSCI Developed Market Index, and those of Brazil, Russia, India, China, and Korea are in MSCI Emerging Market Index. Market capitalizations are as of the end of March 2011 in current USD billions.

Table 2: Properties of Nominal Stock Returns

	U.S.	U.K.	JP	HK	BR	RU	IN	CN	KR
Total Return	-4.7%	-5.1%	-50.0%	51.5%	318.3%	1086.9%	273.6%	90.8%	123.2%
Mean Return	0.04%	0.02%	-0.31%	0.45%	1.33%	2.43%	1.31%	0.92%	0.82%
Volatility	4.7%	4.3%	5.9%	6.4%	7.7%	11.0%	7.7%	8.4%	7.6%
Skewness	-0.55	-0.61	-0.55	-0.37	-0.35	-0.25	-0.22	-0.26	-0.21
Kurtosis	0.73	0.41	0.87	0.90	0.19	1.18	0.98	1.08	0.30

Notes: Total and mean returns are in nominal from January 2000 to March 2011. All measures are computed based on monthly closing prices.

Table 3. Co-integration Relationships by Pairs of Stock Markets

(pair)	Brazil	Russia	India	China	Korea
U.S.	Yes	No	No	No	No/Yes
U.K.	Yes	No	No	No	No
Japan	Yes	No	No/Yes	No	No
HK	Yes	No	No	No	No/Yes
Brazil	-	No	Yes	Yes/No	Yes
Russia	No	-	No	No	No
India	Yes	No	-	No	No/Yes
China	Yes/No	No	No	-	No
Korea	Yes	No	No/Yes	No	-

Notes: ‘Yes’ indicates a co-integration relationship observed either under ADF Case 2 (with mean) or under ADF Case 4 (with mean and time trend). ‘Yes/No’ indicates co-integration test results observed, respectively, based on two estimation horizons: *T=1* / *T=2*, and vice versa. ‘No’ indicates no co-integration relationship under both ADF Case 2 and Case 4, based on both estimation horizons. To check detailed test statistics, please refer to Table 4.

Table 4. Augmented Dickey Fuller Test Results

ADF Case 2 (With Mean)

(T=1)	Brazil		Russia		India		China		Korea	
	T-stats	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**
U.S.	**10.76**	4.04	0.56	3.18	1.30	2.84	2.81	3.81	1.30	2.80
U.K.	**10.66**	4.06	0.63	3.19	1.36	2.87	2.33	3.81	1.64	2.88
Japan	**10.15**	4.08	0.80	3.31	1.26	2.84	1.05	3.85	0.90	2.68
HK	3.68	4.72	1.06	3.25	2.21	3.21	3.32	3.92	1.66	2.92
Brazil	-	-	1.49	2.95	**12.90**	3.79	**9.39**	4.52	**10.92**	3.57
Russia	1.49	2.95	-	-	1.76	3.00	1.06	3.14	1.71	3.40
India	**12.90**	3.79	1.76	3.00	-	-	1.71	3.40	2.41	2.87
China	**9.39**	4.52	1.06	3.14	2.16	3.67	-	-	2.25	3.50
Korea	**10.92**	3.57	1.71	3.40	2.41	2.87	2.25	3.50	-	-

(T=2)	Brazil		Russia		India		China		Korea	
	T-stats	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**
U.S.	**6.55**	4.11	1.79	3.17	1.65	3.25	3.48	4.31	1.42	3.29
U.K.	**10.27**	3.82	1.71	3.22	2.03	3.31	3.81	4.28	1.66	3.41
Japan	**10.15**	3.83	1.90	3.43	2.51	3.18	3.23	4.17	2.77	3.19
HK	**7.63**	4.84	1.68	3.27	3.04	3.72	3.87	4.30	2.01	3.44
Brazil	-	-	2.22	3.31	**4.50**	2.82	0.93	2.56	1.82	2.84
Russia	2.22	3.31	-	-	1.92	3.17	1.82	3.18	1.97	3.43
India	**4.50**	2.82	1.92	3.17	-	-	1.97	3.43	2.60	3.28
China	0.93	2.56	1.82	3.18	2.30	4.10	-	-	2.40	3.97
Korea	1.82	2.84	1.97	3.43	2.60	3.28	2.40	3.97	-	-

ADF Case 4 (With Mean and Trend)

(T=1)	Brazil		Russia		India		China		Korea	
	T-stats	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**
U.S.	**6.55**	4.11	1.79	3.17	1.65	3.25	3.48	4.31	1.42	3.29
U.K.	**10.27**	3.82	1.71	3.22	2.03	3.31	3.81	4.28	1.66	3.41
Japan	**10.15**	3.83	1.90	3.43	2.51	3.18	3.23	4.17	2.77	3.19
HK	**7.63**	4.84	1.68	3.27	3.04	3.72	3.87	4.30	2.01	3.44
Brazil	-	-	1.71	3.24	**10.64**	3.74	**8.32**	4.58	**9.00**	3.50
Russia	1.71	3.24	-	-	1.92	3.17	1.82	3.18	1.97	3.43
India	**10.64**	3.74	1.92	3.17	-	-	1.97	3.43	2.41	2.87
China	**8.32**	4.58	1.82	3.18	2.16	3.67	-	-	2.40	3.97
Korea	**9.00**	3.50	1.97	3.43	2.41	2.87	2.40	3.97	-	-

(T=2)	Brazil		Russia		India		China		Korea	
	T-stats	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**	*T-stats*	*T-stats**
U.S.	2.55	3.26	1.54	3.28	3.44	3.53	1.57	3.00	**3.83**	3.73
U.K.	2.45	3.28	1.49	3.35	3.17	3.29	1.70	2.98	3.41	3.80
Japan	3.13	3.22	2.28	3.57	**3.84**	3.15	1.65	3.14	2.74	3.36
HK	3.04	3.28	1.63	3.68	3.61	3.66	1.93	3.03	**4.37**	3.26
Brazil	-	-	1.94	3.92	**4.49**	3.47	1.92	3.06	**4.03**	3.13
Russia	1.94	3.92	-	-	2.49	4.05	1.37	3.32	2.45	4.00
India	**4.49**	3.47	2.49	4.05	-	-	2.45	4.00	**3.81**	3.31
China	1.92	3.06	1.37	3.32	2.17	3.05	-	-	2.04	3.22
Korea	**4.03**	3.13	2.45	4.00	**3.81**	3.31	2.04	3.22	-	-

Notes: *T-stats** indicates bootstrapped ADF critical values at 90% confidence level. Boldface indicates statistically significant test statistics at 90% confidence level.

Table 5. 2010 OECD's FDI Restrictiveness Index

(closeness=1, open=0)	OECD	Non-OECD	Brazil	**Russia**	India	**China**	Korea
Equity ownership restrictions	0.06	0.10	0.08	**0.22**	0.19	**0.23**	0.14
Screening	0.02	0.01	0.00	**0.04**	0.03	**0.14**	0.00
Operation restrictions	0.01	0.04	0.03	**0.12**	0.00	**0.07**	0.00
Total FDI index	0.10	0.16	0.12	**0.38**	0.22	**0.46**	0.14
Mining	0.15	0.21	0.03	**0.94**	0.53	**0.39**	0.00
Manufacturing	0.04	0.06	0.03	**0.20**	0.03	**0.25**	0.00
Electricity	0.12	0.13	0.03	**0.25**	0.00	**0.61**	0.42
Construction	0.06	0.06	0.03	**0.18**	0.00	**0.27**	0.00
Consumer & Retail	0.06	0.12	0.03	**0.18**	0.42	**0.24**	0.00
Transport	0.25	0.29	0.29	**0.38**	0.17	**0.67**	0.50
Financial Services	0.08	0.05	0.03	**0.53**	0.25	**0.61**	0.20
Real Estate	0.28	0.28	0.00	**0.73**	0.00	**0.28**	0.00

Table 6. Forecasting Ability Diagnostics: Averaged CB Model for China

	1-month	3-month	6-month	12-month
MSPE Ratio$^{(Drift)}$	1.08	1.10	0.59	0.71
(P-value)	(0.46)	(0.34)	(0.23)	**(0.05)**
MSPE Ratio$^{(No\ Drift)}$	1.08	1.11	0.97	0.74
(P-value)	(0.50)	(0.43)	(0.31)	**(0.08)**
Success Ratio	0.45	0.51	0.51	0.61
(P-value)	(0.59)	(0.41)	(0.42)	(0.13)

Note: The initial estimation period is *T=1*, and the forecasting evaluation period is from July 2004 to February 2011. MSPE Ratio—Drift indicates MSPE of the CB model over that of random walk with drift, and MSPE Ratio—No Drift indicates MSPE of the CB model over that of random walk without drift. P-values under the MSPE Ratios are computed based on Clark and West (2006). P-values under the Success Ratio are computed based on Pesaran and Timmermann (2009). Boldface indicates statistically significant p-values at 90% confidence level.

Table 7. Forecasting Ability Diagnostic: Co-integration Based Model for Brazil

		U.S.		U.K.		Japan		Hong Kong		Russia		India		China		Korea	
		T=1	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*
1-month ahead	MSPE Ratio$^{(Drift)}$	0.86	1.01	2.20	1.01	1.91	1.05	1.77	1.04	1.00	1.00	1.54	1.01	0.94	1.01	0.91	1.00
	(P-value)	***(0.06)***	*(0.50)*	***(0.00)***	*(0.51)*	***(0.00)***	*(0.50)*	***(0.00)***	*(0.50)*	*(0.50)*	*(0.50)*	***(0.00)***	*(0.51)*	***(0.02)***	*(0.50)*	***(0.03)***	*(0.51)*
	MSPE Ratio$^{(No\ Drift)}$	1.01	0.98	2.58	0.99	2.23	1.03	2.07	1.02	0.97	0.98	1.80	0.98	1.10	0.98	1.06	0.98
	(P-value)	*(0.51)*	*(0.41)*	*(0.97)*	*(0.38)*	*(0.91)*	*(0.33)*	*(0.91)*	*(0.34)*	*(0.38)*	*(0.44)*	*(0.89)*	*(0.45)*	*(0.63)*	*(0.41)*	*(0.58)*	*(0.43)*
	Success Ratio	0.56	0.64	0.36	0.64	0.36	0.64	0.36	0.64	0.64	0.64	0.36	0.64	0.36	0.64	0.36	0.64
	(P-value)	*(0.64)*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
3-month ahead	MSPE Ratio$^{(Drift)}$	0.81	1.02	3.66	1.05	2.75	1.17	2.51	1.11	0.99	1.01	2.20	1.02	1.02	1.02	0.90	1.01
	(P-value)	***(0.02)***	*(0.52)*	***(0.00)***	*(0.53)*	***(0.00)***	*(0.54)*	***(0.00)***	*(0.50)*	*(0.49)*	*(0.51)*	***(0.00)***	*(0.52)*	***(0.00)***	*(0.51)*	***(0.01)***	*(0.51)*
	MSPE Ratio$^{(No\ Drift)}$	1.08	0.98	4.86	1.01	3.65	1.12	3.32	1.07	0.92	0.97	2.92	0.98	1.35	0.97	1.19	0.97
	(P-value)	*(0.59)*	*(0.36)*	*(1.00)*	*(0.33)*	*(0.99)*	*(0.26)*	*(0.99)*	*(0.24)*	*(0.30)*	*(0.42)*	*(0.99)*	*(0.42)*	*(0.79)*	*(0.36)*	*(0.70)*	*(0.39)*
	Success Ratio	0.40	0.71	0.29	0.71	0.29	0.71	0.29	0.71	0.71	0.71	0.29	0.71	0.29	0.71	0.29	0.71
	(P-value)	*(0.94)*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
6-month ahead	MSPE Ratio$^{(Drift)}$	0.85	1.04	5.25	1.11	3.34	1.40	3.06	1.22	0.99	1.01	2.86	1.03	1.22	1.02	0.96	1.02
	(P-value)	***(0.00)***	*(0.53)*	***(0.00)***	*(0.55)*	***(0.00)***	*(0.60)*	***(0.00)***	*(0.50)*	*(0.49)*	*(0.51)*	***(0.00)***	*(0.52)*	***(0.00)***	*(0.51)*	***(0.00)***	*(0.52)*
	MSPE Ratio$^{(No\ Drift)}$	1.22	0.97	7.55	1.03	4.81	1.30	4.41	1.14	0.88	0.94	4.11	0.96	1.75	0.95	1.38	0.95
	(P-value)	*(0.74)*	*(0.28)*	*(1.00)*	*(0.23)*	*(1.00)*	*(0.15)*	*(1.00)*	*(0.10)*	*(0.22)*	*(0.36)*	*(1.00)*	*(0.35)*	*(0.95)*	*(0.27)*	*(0.84)*	*(0.31)*
	Success Ratio	0.19	0.75	0.25	0.75	0.25	0.75	0.25	0.75	0.75	0.75	0.25	0.75	0.25	0.75	0.25	0.75
	(P-value)	*(1.00)*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
12-month ahead	MSPE Ratio$^{(Drift)}$	1.11	1.07	9.02	1.20	4.39	1.95	4.11	1.57	0.99	1.03	4.55	1.02	1.91	0.97	1.29	1.04
	(P-value)	***(0.00)***	*(0.56)*	***(0.00)***	*(0.61)*	***(0.00)***	*(0.67)*	***(0.00)***	*(0.39)*	*(0.48)*	*(0.53)*	***(0.00)***	*(0.52)*	***(0.00)***	*(0.44)*	***(0.00)***	*(0.56)*
	MSPE Ratio$^{(No\ Drift)}$	1.60	0.94	13.06	1.05	6.35	1.71	5.95	1.37	0.76	0.90	6.58	0.89	2.77	0.85	1.86	0.91
	(P-value)	*(1.00)*	***(0.02)***	*(1.00)*	***(0.00)***	*(1.00)*	***(0.00)***	*(1.00)*	***(0.00)***	***(0.01)***	*(0.13)*	*(1.00)*	***(0.08)***	*(1.00)*	***(0.01)***	*(1.00)*	***(0.06)***
	Success Ratio	0.13	0.78	0.15	0.78	0.15	0.79	0.15	0.76	0.85	0.74	0.15	0.76	0.15	0.76	0.15	0.76
	(P-value)	*(0.99)*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*

Note: The initial estimation period is either *T=1* or *T=2*, and the forecasting evaluation period is from July 2004 to February 2011. MSPE Ratio—Drift indicates MSPE of the CB model over that of random walk with drift, and MSPE Ratio—No Drift indicates MSPE of the CB model over that of random walk without drift. P-values under the MSPE Ratios are computed based on Clark and West (2006). P-values under the Success Ratio are computed based on Pesaran and Timmermann (2009). Boldface indicates statistically significant p-values at 90% confidence level.

Table 8. Forecasting Ability Diagnostic: Co-integration Based Model for Russia

		U.S.		U.K.		Japan		Hong Kong		Brazil		India		China		Korea	
		T=1	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*
1-month ahead	MSPE Ratio$^{(Drift)}$	1.01	1.00	0.99	0.98	0.99	0.99	0.99	0.99	1.00	1.00	0.99	0.99	1.00	0.99	0.98	0.97
	(P-value)	(0.48)	(0.44)	(0.49)	(0.47)	(0.49)	(0.48)	(0.49)	(0.49)	(0.50)	(0.50)	(0.49)	(0.49)	(0.49)	(0.47)	(0.45)	(0.42)
	MSPE Ratio$^{(No\ Drift)}$	0.99	0.99	0.98	0.97	0.98	0.98	0.98	0.98	0.98	0.99	0.98	0.98	0.98	0.98	0.96	0.96
	(P-value)	(0.49)	(0.48)	(0.47)	(0.45)	(0.47)	(0.44)	(0.46)	(0.44)	(0.46)	(0.44)	(0.45)	(0.43)	(0.48)	(0.47)	(0.45)	(0.44)
	Success Ratio	0.48	0.48	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.61	0.61
	(P-value)	(0.22)	(0.22)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	**(0.09)**	**(0.09)**	**(0.04)**	**(0.04)**
3-month ahead	MSPE Ratio$^{(Drift)}$	0.98	0.96	0.97	0.95	0.98	0.96	0.98	0.97	0.99	0.99	0.98	0.98	0.97	0.96	0.92	0.92
	(P-value)	(0.45)	(0.42)	(0.47)	(0.45)	(0.48)	(0.47)	(0.48)	(0.48)	(0.49)	(0.49)	(0.48)	(0.48)	(0.47)	(0.45)	(0.42)	(0.40)
	MSPE Ratio$^{(No\ Drift)}$	0.97	0.97	0.96	0.96	0.97	0.97	0.97	0.98	0.98	1.00	0.97	0.98	0.97	0.97	0.92	0.93
	(P-value)	(0.47)	(0.47)	(0.46)	(0.44)	(0.46)	(0.45)	(0.46)	(0.45)	(0.46)	(0.45)	(0.45)	(0.44)	(0.47)	(0.46)	(0.42)	(0.43)
	Success Ratio	0.48	0.48	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.74	0.71	0.71	0.63	0.63
	(P-value)	(0.14)	(0.14)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	(0.53)	(0.53)	(0.11)	(0.11)
6-month ahead	MSPE Ratio$^{(Drift)}$	0.94	0.90	0.94	0.90	0.95	0.92	0.96	0.94	0.98	0.98	0.96	0.95	0.95	0.92	0.87	0.85
	(P-value)	(0.42)	(0.35)	(0.45)	(0.41)	(0.46)	(0.44)	(0.47)	(0.45)	(0.49)	(0.48)	(0.47)	(0.46)	(0.45)	(0.40)	(0.37)	(0.32)
	MSPE Ratio$^{(No\ Drift)}$	0.95	0.93	0.95	0.93	0.96	0.96	0.97	0.98	0.99	1.01	0.97	0.99	0.96	0.95	0.88	0.88
	(P-value)	(0.45)	(0.43)	(0.44)	(0.41)	(0.45)	(0.42)	(0.45)	(0.43)	(0.45)	(0.43)	(0.44)	(0.42)	(0.45)	(0.44)	(0.38)	(0.39)
	Success Ratio	0.54	0.54	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.76	0.76	0.70	0.70
	(P-value)	**(0.02)**	**(0.02)**	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	(0.41)	(0.41)	**(0.01)**	**(0.01)**
12-month ahead	MSPE Ratio$^{(Drift)}$	0.88	0.78	0.90	0.80	0.93	0.85	0.94	0.89	0.96	0.95	0.94	0.92	0.95	0.89	0.82	0.73
	(P-value)	(0.31)	(0.14)	(0.38)	(0.29)	(0.42)	(0.34)	(0.43)	(0.39)	(0.45)	(0.45)	(0.44)	(0.43)	(0.43)	(0.30)	(0.27)	(0.13)
	MSPE Ratio$^{(No\ Drift)}$	0.89	0.84	0.91	0.86	0.94	0.91	0.95	0.96	0.97	1.02	0.95	0.99	0.96	0.96	0.83	0.79
	(P-value)	(0.34)	(0.27)	(0.35)	(0.21)	(0.38)	(0.22)	(0.38)	(0.24)	(0.36)	(0.22)	(0.35)	(0.23)	(0.42)	(0.39)	(0.26)	(0.21)
	Success Ratio	0.61	0.61	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.76	0.76	0.78	0.78
	(P-value)	**(0.02)**	**(0.02)**	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	**(0.01)**	**(0.01)**

Note: See Table 7.

Table 9. Forecasting Ability Diagnostic: Co-integration Based Model for India

		U.S.		U.K.		Japan		Hong Kong		Brazil		Russia		China		Korea	
		T=1	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*
1-month ahead	MSPE Ratio$^{(Drift)}$	1.01	1.01	1.18	1.03	1.02	1.01	1.00	1.01	1.01	1.00	1.00	1.01	1.00	1.00	1.02	1.01
	(P-value)	(0.52)	(0.50)	(0.50)	(0.52)	(0.48)	(0.50)	(0.48)	(0.50)	(0.51)	(0.50)	(0.50)	(0.51)	(0.50)	(0.48)	(0.52)	(0.51)
	MSPE Ratio$^{(No\ Drift)}$	0.98	1.00	1.14	1.02	0.99	1.00	0.96	0.99	0.99	0.99	0.98	1.00	0.98	0.99	0.98	0.99
	(P-value)	(0.39)	(0.43)	(0.65)	(0.44)	(0.47)	(0.50)	(0.42)	(0.49)	(0.47)	(0.45)	(0.45)	(0.49)	(0.44)	(0.41)	(0.44)	(0.46)
	Success Ratio	0.66	0.64	0.34	0.65	0.65	0.58	0.66	0.61	0.66	0.65	0.66	0.60	0.66	0.64	0.66	0.61
	(P-value)	N/A	N/A	N/A	N/A	**(0.00)**	**(0.00)**	N/A	(1.00)	N/A	(1.00)	N/A	(0.69)	N/A	N/A	N/A	(1.00)
3-month ahead	MSPE Ratio$^{(Drift)}$	1.04	1.03	1.46	1.10	1.05	1.02	1.00	1.01	1.08	1.00	1.00	1.02	1.01	1.01	1.05	1.02
	(P-value)	(0.55)	(0.52)	(0.49)	(0.59)	(0.46)	(0.47)	(0.47)	(0.49)	(0.57)	(0.50)	(0.50)	(0.52)	(0.51)	(0.48)	(0.55)	(0.52)
	MSPE Ratio$^{(No\ Drift)}$	0.96	1.01	1.34	1.08	0.96	1.00	0.92	0.99	1.03	0.98	0.95	1.00	0.97	0.99	0.97	1.00
	(P-value)	(0.31)	(0.37)	(0.76)	(0.44)	(0.44)	(0.50)	(0.36)	(0.48)	(0.54)	(0.42)	(0.39)	(0.47)	(0.40)	(0.33)	(0.40)	(0.43)
	Success Ratio	0.69	0.68	0.31	0.66	0.63	0.54	0.69	0.61	0.41	0.68	0.69	0.61	0.69	0.68	0.69	0.65
	(P-value)	N/A	N/A	N/A	(1.00)	**(0.06)**	(0.19)	N/A	N/A	(0.99)	N/A	N/A	(0.93)	N/A	N/A	N/A	(1.00)
6-month ahead	MSPE Ratio$^{(Drift)}$	1.07	1.07	1.63	1.23	1.08	1.03	1.02	1.02	1.19	1.00	0.99	1.02	1.01	0.99	1.07	1.03
	(P-value)	(0.58)	(0.55)	(0.50)	(0.72)	(0.46)	(0.45)	(0.47)	(0.48)	(0.64)	(0.50)	(0.48)	(0.52)	(0.51)	(0.44)	(0.57)	(0.54)
	MSPE Ratio$^{(No\ Drift)}$	0.94	1.03	1.43	1.18	0.95	0.99	0.90	0.98	1.09	0.96	0.92	0.98	0.95	0.95	0.94	0.99
	(P-value)	(0.21)	(0.28)	(0.84)	(0.50)	(0.41)	(0.48)	(0.31)	(0.45)	(0.63)	(0.35)	(0.33)	(0.42)	(0.35)	(0.19)	(0.32)	(0.36)
	Success Ratio	0.79	0.79	0.21	0.76	0.69	0.65	0.79	0.79	0.18	0.79	0.79	0.70	0.79	0.79	0.79	0.79
	(P-value)	N/A	N/A	N/A	(0.99)	**(0.02)**	**(0.00)**	N/A	N/A	(0.99)	N/A	N/A	(0.58)	N/A	N/A	N/A	N/A
12-month ahead	MSPE Ratio$^{(Drift)}$	1.14	1.16	2.18	1.44	1.17	1.06	1.05	1.03	1.32	0.99	1.00	1.03	1.00	0.95	1.14	1.07
	(P-value)	(0.62)	(0.60)	(0.50)	(0.86)	(0.47)	(0.41)	(0.47)	(0.45)	(0.75)	(0.49)	(0.49)	(0.52)	(0.49)	(0.34)	(0.62)	(0.58)
	MSPE Ratio$^{(No\ Drift)}$	0.87	1.07	1.67	1.33	0.90	0.98	0.81	0.95	1.14	0.92	0.88	0.95	0.86	0.88	0.88	0.99
	(P-value)	**(0.03)**	**(0.06)**	(0.97)	(0.56)	(0.29)	(0.45)	(0.13)	(0.38)	(0.73)	(0.16)	(0.22)	(0.30)	(0.14)	**(0.01)**	(0.13)	(0.19)
	Success Ratio	0.85	0.78	0.15	0.85	0.70	0.59	0.85	0.75	0.25	0.75	0.85	0.71	0.85	0.75	0.85	0.75
	(P-value)	N/A	N/A	N/A	N/A	**(0.08)**	(0.13)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Note: See Table 7.

Table 10. Forecasting Ability Diagnostic: Co-integration Based Model for China

		U.S.		U.K.		Japan		Hong Kong		Brazil		Russia		India		Korea	
		T=1	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*
1-month ahead	MSPE Ratio$^{(Drift)}$	1.13	1.03	0.98	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.01	1.00
	(P-value)	(0.56)	(0.54)	(0.46)	(0.47)	(0.48)	(0.48)	(0.48)	(0.49)	(0.45)	(0.50)	(0.49)	(0.48)	(0.47)	(0.49)	(0.50)	(0.49)
	MSPE Ratio$^{(No\ Drift)}$	1.13	1.04	0.98	1.00	0.99	1.00	0.99	1.01	1.01	1.01	1.00	1.00	0.99	1.01	1.01	1.01
	(P-value)	(0.61)	(0.56)	(0.46)	(0.49)	(0.48)	(0.49)	(0.48)	(0.50)	(0.44)	(0.50)	(0.50)	(0.51)	(0.45)	(0.48)	(0.51)	(0.52)
	Success Ratio	0.44	0.43	0.63	0.61	0.63	0.60	0.63	0.60	0.63	0.60	0.60	0.38	0.63	0.59	0.43	0.44
	(P-value)	(0.11)	(0.66)	N/A	(0.11)	N/A	(0.17)	N/A	(0.17)	N/A	(0.17)	(0.87)	(0.74)	N/A	(0.31)	**(0.06)**	(0.47)
3-month ahead	MSPE Ratio$^{(Drift)}$	1.20	1.09	0.96	0.96	0.97	0.98	0.99	0.99	1.01	1.01	0.99	0.97	0.99	1.01	1.01	0.99
	(P-value)	(0.55)	(0.63)	(0.41)	(0.43)	(0.45)	(0.45)	(0.47)	(0.48)	(0.44)	(0.51)	(0.47)	(0.43)	(0.45)	(0.49)	(0.47)	(0.45)
	MSPE Ratio$^{(No\ Drift)}$	1.21	1.14	0.97	1.00	0.98	1.02	1.00	1.03	1.03	1.05	1.00	1.01	1.00	1.05	1.02	1.03
	(P-value)	(0.67)	(0.70)	(0.42)	(0.49)	(0.46)	(0.52)	(0.47)	(0.54)	(0.42)	(0.56)	(0.51)	(0.52)	(0.42)	(0.53)	(0.52)	(0.55)
	Success Ratio	0.55	0.48	0.54	0.54	0.54	0.55	0.54	0.55	0.54	0.54	0.49	0.51	0.54	0.54	0.56	0.48
	(P-value)	**(0.00)**	(0.54)	N/A	(0.40)	N/A	(0.35)	N/A	(0.35)	N/A	(0.40)	N/A	N/A	N/A	(0.41)	N/A	(0.51)
6-month ahead	MSPE Ratio$^{(Drift)}$	1.11	1.14	0.93	0.94	0.95	0.96	0.98	0.99	1.02	1.02	0.97	0.92	0.99	1.04	0.99	0.95
	(P-value)	(0.48)	(0.66)	(0.38)	(0.40)	(0.43)	(0.44)	(0.47)	(0.48)	(0.47)	(0.53)	(0.43)	(0.36)	(0.46)	(0.53)	(0.44)	(0.39)
	MSPE Ratio$^{(No\ Drift)}$	1.14	1.25	0.96	1.03	0.98	1.06	1.01	1.08	1.05	1.12	1.01	1.01	1.02	1.14	1.02	1.04
	(P-value)	(0.62)	(0.80)	(0.41)	(0.53)	(0.45)	(0.57)	(0.48)	(0.61)	(0.46)	(0.65)	(0.52)	(0.51)	(0.44)	(0.63)	(0.52)	(0.56)
	Success Ratio	0.56	0.44	0.55	0.54	0.55	0.54	0.55	0.53	0.55	0.54	0.50	0.50	0.55	0.54	0.55	0.50
	(P-value)	N/A	(0.65)	N/A	(0.40)	N/A	(0.40)	N/A	(0.44)	N/A	(0.40)	(1.00)	N/A	N/A	(0.42)	N/A	(0.29)
12-month ahead	MSPE Ratio$^{(Drift)}$	0.98	0.94	0.90	0.96	0.94	0.99	0.97	1.01	1.02	1.07	0.95	0.85	0.98	1.15	0.94	0.84
	(P-value)	(0.24)	(0.29)	(0.36)	(0.45)	(0.42)	(0.49)	(0.45)	(0.51)	(0.45)	(0.58)	(0.41)	(0.28)	(0.44)	(0.65)	(0.37)	(0.26)
	MSPE Ratio$^{(No\ Drift)}$	1.02	1.10	0.94	1.13	0.98	1.16	1.01	1.18	1.07	1.25	1.01	0.99	1.02	1.35	0.98	0.98
	(P-value)	(0.37)	(0.50)	(0.40)	(0.63)	(0.46)	(0.68)	(0.48)	(0.70)	(0.42)	(0.75)	(0.52)	(0.48)	(0.44)	(0.80)	(0.46)	(0.45)
	Success Ratio	0.64	0.60	0.48	0.40	0.48	0.39	0.48	0.39	0.48	0.39	0.43	0.58	0.48	0.41	0.63	0.63
	(P-value)	N/A	**(0.08)**	N/A	(0.83)	N/A	(0.86)	N/A	(0.86)	N/A	(0.86)	N/A	N/A	N/A	(0.80)	N/A	N/A

Note: See Table 7.

Table 11. Forecasting Ability Diagnostic: Co-integration Based Model for Korea

		U.S.		U.K.		Japan		Hong Kong		Brazil		Russia		India		China	
		T=1	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*	*T=1*	*T=2*
1-month ahead	MSPE Ratio$^{(Drift)}$	1.03	1.01	0.99	1.00	1.00	1.00	1.00	1.00	1.01	1.00	0.99	1.01	0.99	1.00	1.00	1.00
	(P-value)	(0.52)	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)	(0.52)	(0.50)	(0.47)	(0.51)	(0.49)	(0.50)	(0.50)	(0.50)
	MSPE Ratio$^{(No\ Drift)}$	1.00	1.00	0.97	0.99	0.97	0.99	0.97	0.99	1.00	0.99	0.98	1.01	0.98	0.99	0.98	1.00
	(P-value)	(0.50)	(0.51)	(0.41)	(0.47)	(0.43)	(0.48)	(0.42)	(0.48)	(0.50)	(0.46)	(0.46)	(0.51)	(0.45)	(0.46)	(0.46)	(0.49)
	Success Ratio	0.49	0.49	0.61	0.60	0.61	0.59	0.61	0.59	0.54	0.60	0.56	0.48	0.61	0.60	0.61	0.61
	(P-value)	**(0.05)**	**(0.05)**	N/A	N/A	N/A	(0.90)	N/A	(0.90)	(1.00)	N/A	(0.20)	(0.93)	N/A	N/A	(0.17)	(0.17)
3-month ahead	MSPE Ratio$^{(Drift)}$	1.07	1.03	0.98	0.99	1.00	1.00	1.00	1.00	1.03	1.00	0.97	1.03	0.99	1.00	1.01	1.01
	(P-value)	(0.53)	(0.48)	(0.48)	(0.48)	(0.50)	(0.49)	(0.50)	(0.50)	(0.54)	(0.50)	(0.43)	(0.51)	(0.47)	(0.50)	(0.50)	(0.50)
	MSPE Ratio$^{(No\ Drift)}$	1.01	1.02	0.92	0.97	0.94	0.99	0.94	0.99	1.01	0.99	0.94	1.02	0.97	0.99	0.97	1.00
	(P-value)	(0.50)	(0.52)	(0.33)	(0.44)	(0.37)	(0.46)	(0.35)	(0.45)	(0.50)	(0.43)	(0.41)	(0.52)	(0.40)	(0.42)	(0.41)	(0.48)
	Success Ratio	0.43	0.43	0.73	0.73	0.73	0.68	0.73	0.69	0.68	0.70	0.71	0.51	0.73	0.70	0.70	0.70
	(P-value)	(0.22)	(0.22)	N/A	N/A	N/A	N/A	N/A	N/A	(0.44)	N/A	**(0.00)**	(0.83)	N/A	N/A	(0.29)	(0.29)
6-month ahead	MSPE Ratio$^{(Drift)}$	1.09	1.04	0.97	0.97	0.99	0.99	1.00	1.00	1.04	1.01	0.96	1.04	0.98	1.01	1.03	1.02
	(P-value)	(0.52)	(0.44)	(0.46)	(0.46)	(0.49)	(0.48)	(0.50)	(0.50)	(0.55)	(0.51)	(0.42)	(0.50)	(0.46)	(0.51)	(0.52)	(0.51)
	MSPE Ratio$^{(No\ Drift)}$	1.00	1.03	0.89	0.96	0.92	0.97	0.92	0.98	1.02	0.99	0.94	1.02	0.96	1.00	0.98	1.00
	(P-value)	(0.50)	(0.52)	(0.27)	(0.40)	(0.33)	(0.42)	(0.31)	(0.42)	(0.51)	(0.40)	(0.40)	(0.53)	(0.38)	(0.39)	(0.40)	(0.48)
	Success Ratio	0.49	0.49	0.73	0.73	0.73	0.73	0.73	0.73	0.63	0.73	0.74	0.46	0.73	0.73	0.70	0.70
	(P-value)	(0.10)	(0.10)	N/A	N/A	N/A	N/A	N/A	N/A	(0.65)	N/A	**(0.01)**	(0.84)	N/A	N/A	(0.29)	(0.29)
12-month ahead	MSPE Ratio$^{(Drift)}$	1.15	1.11	0.93	0.94	0.99	0.97	1.00	0.99	1.05	1.01	1.03	1.04	0.93	1.04	1.12	1.13
	(P-value)	(0.52)	(0.33)	(0.40)	(0.42)	(0.48)	(0.45)	(0.49)	(0.49)	(0.58)	(0.51)	(0.47)	(0.39)	(0.32)	(0.53)	(0.59)	(0.60)
	MSPE Ratio$^{(No\ Drift)}$	0.98	1.02	0.79	0.87	0.84	0.89	0.85	0.92	1.02	0.94	0.98	0.96	0.91	0.96	1.05	1.05
	(P-value)	(0.44)	(0.47)	**(0.05)**	(0.16)	(0.13)	(0.17)	**(0.10)**	(0.17)	(0.48)	(0.12)	(0.45)	(0.42)	(0.17)	(0.11)	(0.32)	(0.48)
	Success Ratio	0.55	0.55	0.81	0.81	0.81	0.79	0.81	0.80	0.55	0.79	0.78	0.70	0.81	0.81	0.74	0.74
	(P-value)	N/A	N/A	N/A	N/A	N/A	(0.98)	N/A	N/A	N/A	(0.98)	**(0.01)**	**(0.01)**	N/A	N/A	(0.72)	(0.72)

Note: See Table 7.