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A Bootstrap Analysis of the Nikkei 225

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Abstract

This study intends to find out whether or not the Nikkei 225 evolves over time in accordance with the following four widely used processes for determining stock prices: random walk with a drift, AR(1), GARCH(1,1), and GARCH(1,1)-M. Given the fact that, in actuality, we have but one sample of time series data, the motivation of this study is to make use of the bootstrap technology to deal with this one-sample problem. Specifically, we use the bootstrap technique to generate 2,000 artificial Nikkei series from each process and compute the return from the trading rule for each of the 2,000 artificial Nikkei series. Then, we construct a 95% bootstrap percentile interval with these 2,000 returns and determine if it contains the return computed from the actual Nikkei series. If it does, we claim that returns from the artificial Nikkei series are in agreement with those from the actual Nikkei series. Our results show that, of the four processes, GARCH(1,1)-M generates returns that are most agreeable with those computed from the actual Nikkei series. An important implication of this study is that a proper model for pricing Nikkei-related derivatives is one that uses the GARCH(1,1)-M process to depict the dynamics of the Nikkei return series.

JEL Classifications: C15, C22, G15
Key Words: Nikkei 225, Bootstrap method, Simple Moving Average, Return-generating processes, Bootstrap percentile interval

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I. Introduction

Over the years, the Japanese stock market has been consistently classified as a developed market by FTSE Group's list, MSCI list, Dow Jones list, Russell Global list, the International Finance Corporation, and the Global Stock Markets Factbook. As a matter of fact, the Japanese stock market has undergone a series of reforms since the 1990s. In particular, in November 1996, Prime Minister Ryutaro Hashimoto initiated a comprehensive reform package, often referred to as the Japanese Big Bang[1], with the objective of creating a "free, fair, and global" financial market. According to the prime minister, "free" means creating a market in which market principles prevail; "fair" means enhancing the fairness and transparency of the market through clearly defined accounting and supervisory rules; and "global" means reforming the market in line with international standards. Thanks to the reforms implemented during the 1990s, many studies (e.g., Cajueiro and Tabak, 2004; Worthington and Higgs, 2006; Lim, 2007; Chong and Chan, 2008) have provided empirical evidence that the Japanese stock market has become more efficient.

The above said, it is important to study how the Japanese stock market – one of the largest markets in the world in terms of trading volume and market capitalization - evolved before and after those financial reforms were implemented in the 1990s. Specifically, this study aims to find out whether or not the Nikkei 225 (henceforth referred to as the Nikkei), the benchmark indicator of the Japanese stock market, evolves over time in accordance with some widely used random processes for stock prices. Accordingly, by means of a simple moving average trading rule, we employ the bootstrap method of Efron (1979, 1982) to investigate how closely returns from the Nikkei are in agreement with returns generated from the following four widely used random processes for stock prices: a random walk with a drift RW(α)), an autoregressive process of order one (AR(1)), and two generalized autoregressive conditional heteroscedastic models - (GARCH(1,1) and GARCH(1,1)-M). Given the importance of the Nikkei, the implication of this study is that, for participants (e.g., investors, speculators, and hedgers) in the Japanese stock market, a better knowledge of the dynamics of the index is crucial for appropriately managing stock market risk and correctly pricing Nikkei-related derivatives[2].

However, for time series data, we are constrained by the fact that we have only one historical sample. Hence, it is hardly surprising that previous empirical findings[3] based on different

[1] One major focus of the Japanese Big Bang reform was on institutional changes. These changes included the following two broad areas: (1) Improving the efficiency and competitiveness of domestic financial institutions (e.g., foreign financial companies were allowed to operate more freely in Japan); and (2) Abolishing monopoly powers previously enjoyed by domestic banks, securities companies, and insurance firms (e.g., domestic and foreign financial institutions would compete on an equal footing for Japan's multi-trillion pension fund business). For details, see Craig (1998) and Hall (1998).

[2] Some Nikkei-related derivatives include the Nikkei 225 index options traded on the Osaka Securities Exchange and the Singapore Exchange, and the Nikkei 225 warrants traded on the American and Toronto Stock Exchanges.

[3] For example, Alexander (1961, 1964), Jensen and Benington (1970), Bollerslev (1986), Engle, *et al*. (1987), French, *et al*. (1987), Chou (1988), Conrad and Kaul (1988, 1989), Bollerslev, *et al*. (1992), and Tsay (2005).

time series data are, to a certain extent, divided on asset price dynamics. Accordingly, the motivation of this study is to make use of bootstrap technology to deal with this “one sample” problem. Simply put, in the context of this study, the bootstrap enables us to generate at random a large number of samples (2,000 samples in this study) through replacement with each of the above four random processes such that each of these so-called bootstrap samples (i.e., artificial Nikkei series) will possess the same statistical properties as the actual Nikkei series. Using these 2,000 artificial Nikkei series for constructing a 95% bootstrap percentile interval, we can investigate how closely returns from the actual Nikkei series match returns generated from each of the four processes.

The logic of our bootstrap implementation can better be understood from another perspective. Suppose the Nikkei literally evolves through time according to, say, a random walk with a drift (i.e., RW(α)). Then, the actual Nikkei series is simply a sample drawn from this RW(α) process. Hence, it is highly likely that the return computed from this actual Nikkei series will fall within the 95% bootstrap percentile interval constructed using the 2,000 returns generated from this RW(α) process.

The rest of the paper proceeds as follows: Section II describes the Nikkei price series and gives a description of the simple moving average trading rule. Section III describes our bootstrap method, presents reasons for using the four return-generating processes, and uses an illustration to show how to implement our bootstrap by which artificial Nikkei price series are generated for each of the four processes. In Section IV, we present and discuss our empirical results. In Section V, we conclude this study and outline the implications of this research.

II. Data and Simple Moving Average Trading Rule

A. The Nikkei Data Series

The data used are daily closing prices of the Nikkei (see Figure 1) from January 1, 1971, to December 31, 2010 – a total of 10,436 observations. They were retrieved from the DataStream database. Since no major financial reform was implemented in Japan before the 1990s, we partition the entire sample period into two equal sub-periods[4]: 1971-1990 and 1991-2010. We compute the daily return as the natural log difference of the Nikkei prices. That is,

$$R_t = \log(P_t) - \log(P_{t-1}) \qquad (1)$$

[4] The 1971-1990 sub-period is the time when the Japanese stock market moved forward at full speed; the 1991-2010 sub-period is the time which is often referred to as the two lost decades of Japan.

where P_{t-1} and P_t are the closing prices of the Nikkei on day *t-1* and day *t*, and R_t is the return for the time from day *t-1* to day *t*.

In an efficient market, security returns are independent of one another over time because new information comes to the market in a random and unpredictable manner, and security prices respond instantly and accurately to this new information. Hence, the magnitude of the autocorrelation in security returns can offer some clues as to the efficiency of the market. Simply put, autocorrelation should be insignificant if the market is efficient. From Table 1, we note that the daily autocorrelation for 1971-1990 is statistically significant at the 1% level at lags 1, 2, 3, and 5, whereas that for 1991-2010 is statistically significant at the 1% level only at lag 1. In other words, for the earlier sub-period, the return on day *t* is likely to depend on returns on days *t-1*, *t-2*, *t-3*, and *t-5*; whereas for the later sub-period, the return on day *t* is likely to depend only on the return on day *t-1*. Hence, the autocorrelations provide a rough indication that the Japanese stock market displayed relatively greater efficiency for the 1991-2010 sub-period.

B. The Trading Rule

The trading rule used in this study is the Simple Moving Average[5] (SMA). The n-day Moving Average (MA) on day *t* is

$$M_{t,n} = \frac{1}{n}\sum_{k=t-n+1}^{t} P_k = \frac{1}{n}\left[P_{t-n+1} + P_{t-n+2} + \ldots + P_{t-1} + P_t\right] \tag{2}$$

where P_k is the closing price of the Nikkei on day *k*.

According to SMA rules, a buy signal is generated when the closing price rises above the *n*-day MA and a sell signal is generated when the closing price falls below the *n*-day MA. That is, an investor would take a long position in the Nikkei when a buy signal is generated and, conversely, a short position in the Nikkei when a sell signal is generated. When a signal is generated, SMA rules require that the position be maintained until the closing price penetrates the n-day MA again. A commonly used SMA rule is 1-100, where the MA is 100 days. In this study, we use the following SMA rules: (1, 20), (1, 50), (1, 100), and (1, 200). Each rule is evaluated with bands of 0% and 1%, making a total of eight SMA rules. A band is used to reduce the number of times an investor would have to move into and out of the market. For example, Brock et al. (1992), Bessembinder and Chan (1998), and Siegel (2002) all use a 1% band for their SMA rules.

[5] See Edwards, *et al*. (2007) for details on the simple moving average and other trading rules.

III. Bootstrap Implementation

In this section, we first give a simple description of the bootstrap method[6] customized for this study; then, we point out why it is justifiable to use the four random processes for generating artificial Nikkei series; and finally, we make use of an illustration to show how to implement our bootstrap by which artificial Nikkei price series are generated for each of the four processes.

A. The Bootstrap Method

For our bootstrap implementation, we apply each of the four random processes to the actual Nikkei return series to obtain their respective estimated parameters (e.g., α in RW(α)) and residuals. The residuals are then redrawn with replacement to form a scrambled residual series which is then used with the estimated parameters to generate artificial Nikkei return series such that each of these so-called bootstrap samples (i.e., artificial Nikkei series) will possess the same statistical properties as the actual Nikkei series. In this study, the relevant statistic is the return from the 2000SMA trading rule computed from the Nikkei seriesseries. Specifically, we use the bootstrap to generate 2,000 artificial Nikkei series[7] from each of the four processes and compute the return from the SMA trading rule for each of these 2,000 artificial Nikkei series. Then, following on from Efron and Tibshirani (1993), we construct a 95% bootstrap percentile interval with these 2,000 returns. If the return from the SMA rule computed from the actual Nikkei series falls within this 95% percentile interval, then we claim that this return agrees with those generated from the artificial Nikkei series and, furthermore, infer that the actual Nikkei series is in agreement with those artificial Nikkei series generated for a given random process. In other words, the actual Nikkei series is like a sample drawn from this process.

B. The Four Return-Generating Processes

The four random processes[8] for generating artificial Nikkei return series are as follows:

RW(α)	$R_t = \alpha + \varepsilon_t$	(3)
AR(1)	$R_t = \alpha + \beta R_{t-1} + \varepsilon_t$	(4)
GARCH(1,1)	$R_t = \alpha + \varepsilon_t$	(5)

[6] See Efron and Tibshirani (1993) for details.

[7] According to Efron and Tibshirani (1993), 2,000 artificial Nikkei series are more than enough for estimation accuracy purposes.

[8] Alternatively, we can write the four processes in a compact form as $R_t = u_t + \varepsilon_t$, where $u_t = \alpha$ in RW(α) and GARCH(1,1); $u_t = \alpha + \beta R_{t-1}$ in AR(1); and $u_t = \alpha + \beta\sigma_t^2$ in GARCH(1,1)-M.

GARCH(1,1)-M[9] $$R_t = \alpha + \beta\sigma_t^2 + \varepsilon_t \quad (6)$$

For equations (3) and (4), ε_t is independently and identically distributed. For equations (5) and (6), $\sigma_t^2 = a + b\varepsilon_{t-1}^2 + c\sigma_{t-1}^2$, $\varepsilon_t = \sigma_t z_t$, and $z_t \sim N(0,1)$. That is, R_t is the return on day t, ε_t is normally distributed and serially uncorrelated, z_t is normally[10] distributed with zero mean and unit variance, and σ_t^2 is a linear function of the square of the last period's error (i.e., ε_{t-1}) and of the last period's conditional variance (i.e., σ_{t-1}^2). Note that if β in equation (6) is positive and statistically significant, then increased risk (as measured by an increase in the conditional variance σ_t^2) results in an increase in return R_t. Hence, β can be regarded as the amount of risk.

We choose the four random processes because they have been found by numerous studies to best characterize the dynamics of asset/stock returns. These four encompass a wide range of random processes commonly used for asset/stock returns. At this juncture, some related references are in order. For the RW(α) process, Fama (1995) claims that "the empirical evidence to date provides strong support for the random walk model." For the AR(1) process[11], Conrad and Kaul (1989) show that a first-order autocorrelation of 0.20 is found for a value-weighted portfolio of the largest companies over the 1962-1985 period, and that higher order autocorrelation beyond a lag of one day is basically zero. For the GARCH (1,1) process, Brooks (2008) states that "in general a GARCH(1,1) model will be sufficient to capture the volatility clustering in the data, and rarely is any higher order model estimated or even entertained in the academic finance literature." For the GARCH(1,1)-M process, Chou (1988) fits such a process to the weekly returns of the NYSE value-weighted index over the 1962-1985 period and finds the existence of changing equity premiums. For details, see Alexander (1961, 1964), Fama (1965, 1970, 1995), and Jensen and Benington (1970) for random walks; Conrad and Kaul (1988, 1989) and Tsay (2005) for the AR(1) process; and Bollerslev (1986), Engle et al. (1987), French et al. (1987), Chou (1988), Bollerslev et al. (1992), and Brook (2008) for the two GARCH processes.

C. An Illustration

As an illustration, we use an AR(1) process to demonstrate how to implement our bootstrap by taking the following steps. (i) Based on the actual Nikkei return series, we estimate the two parameters in equation (4) using the ordinary least squares method and obtain the

[9] The GARCH(1,1)-M process can also be expressed in such a form that the conditional mean is linear in the conditional standard deviation σ_t rather than in the conditional variance σ_t^2.

[10] An alternative to a standard normal distribution is to assume that z_t follows a standard Student's *t* distribution, in which case the *t* density has more probability mass in the tails.

[11] In this study, a major reason for using an AR(1) process is that the autocorrelations for daily returns from the Nikkei over the two sub-periods are both statistically significant at the 1% level at lag 1. See Table 1.

two estimates $\hat{\alpha}$ and $\hat{\beta}$. (ii) We compute the residual as $e_t = R_t - \hat{R}_t$, where t = 1, 2, …, N and $\hat{R}_t = \hat{\alpha} + \hat{\beta} R_{t-1}$. Hence, we obtain a series of residuals; that is, $\{e_1, e_2, \ldots, e_N\}$. (iii) For each j, we randomly draw a residual with replacement from the residual series and form $R_j = \hat{\alpha} + \hat{\beta} R_{j-1} + e_j$(where j = 1, 2, …, N) to generate an artificial AR(1) Nikkei return series. (iv) We convert each artificial AR(1) Nikkei return series into an artificial AR(1) Nikkei price series using equation (1). (v) Similar to computing the daily return from the SMA rule using actual Nikkei price series, we compute the daily return from the SMA rule for buy and for sell using artificial AR(1) Nikkei price series. (vi) Repeating steps (i) – (v), we obtain 2,000 daily returns (denoted by $R_1^b, R_2^b, \ldots, R_{2000}^b$) for buy and 2,000 daily returns (denoted by $R_1^s, R_2^s, \ldots, R_{2000}^s$) for sell computed respectively from 2,000 artificial AR(1) Nikkei price series.

Following Efron and Tibshirani (1993), we construct a 95% bootstrap percentile interval such that the 2.5th percentile and 97.5th percentile of the 2,000 daily returns (for buy and for sell) computed from artificial Nikkei price series are, respectively, the lower and upper limits for the interval. Specifically, arranging the 2,000 daily returns in ascending order such that $R_{(1)}^b \le R_{(2)}^b \le \ldots \le R_{(1999)}^b \le R_{(2000)}^b$ for buy and $R_{(1)}^s \le R_{(2)}^s \le \ldots \le R_{(1999)}^s \le R_{(2000)}^s$ for sell, we find that the 95% bootstrap interval[12] is $\left[R_{(51)}^b, R_{(1950)}^b\right]$ for buy and $\left[R_{(51)}^s, R_{(1950)}^s\right]$ for sell. That said, we determine if the daily return (for buy and for sell) from each SMA rule computed from the actual Nikkei price series lies within this 95% bootstrap interval.

IV. Empirical Results

We use the ordinary least squares method to estimate the parameters of the RW(α) and AR(1) processes, and the maximum likelihood method to estimate the parameters of the GARCH(1,1) and GARCH(1,1)-M processes. Table 2 presents the parameter estimates for the four processes over the two sub-periods. The parameters are estimated using the RATS econometric package. Table 3 shows the daily returns from the eight SMA rules based on actual Nikkei price series. For 1971-1990, each of the eight rules results in a positive daily return for buy and a negative daily return for sell, suggesting that the market tended to move upward over this sub-period. For 1991- 2010, each of the eight rules results in a daily return for buy smaller than that for sell, implying that the market tended to move downward over this sub-period. In the following sections, we will determine if the daily returns from the eight SMA rules in Table 3 computed from the actual Nikkei price series lie within their respective 95% bootstrap percentile intervals under each of the four processes.

In Tables 4-7, for each of the eight SMA rules, "Mean" is the average value of the 2,000

[12] That is, $R_{(51)}^b$ and $R_{(1950)}^b$ are the 2.5th and 97.5th percentiles of the 2,000 daily returns for buy; $R_{(51)}^s$ and $R_{(1950)}^s$ are the 2.5th and 97.5th percentiles of the 2,000 daily returns for sell.

daily returns computed from artificial Nikkei price series, "$R_{(51)}$" and "$R_{(1950)}$" denote the 2.5th and 97.5th percentiles of the 2,000 daily returns for buy and for sell. For example, considering the (1, 20, 0%) rule for buy in the first three rows of Table 4, 0.000173 is the average value of the 2,000 daily returns, and -0.000039 and 0.000404 are the 2.5th and 97.5th percentiles of the 2,000 daily returns. That is, [-0.000039, 0.000404] is a 95% bootstrap confidence interval. For visual clarity, those 95% intervals are shaded if the daily returns in Table 3 computed from the actual Nikkei price series lie within their respective intervals.

A. Results based on Artificial RW(α) Nikkei Series

Table 4 shows the daily returns from the eight SMA rules based on the artificial Nikkei price series generated from the random walk process for the two sub-periods. For 1971-1990, none of the eight SMA rules for buy results in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals; but three of the eight SMA rules for sell result in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals. That is, the (1, 20, 0%), (1, 50, 0%), and (1, 100, 0%) rules for sell result in the daily returns of -0.000217, -0.000117, and -0.000068 (see Table 3) from the actual Nikkei series lying within [-0.000507, -0.000084], [-0.000452, -0.000041], and [-0.000512, -0.000066], respectively. For 1991-2010, four SMA rules for buy and five SMA rules for sell result in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals.

In comparison, daily returns computed from the actual Nikkei series appear more likely to have been generated from the RW(α) process for the 1991-2010 sub-period than for the 1971-1990 sub-period. Given the fact that the Japanese stock market has become more efficient (see Section I) after a series of financial reforms were implemented during the 1990s, it is no surprise that the Nikkei evolved over the second sub-period as if it were a sample likely drawn from the RW(α) process.

B. Results based on Artificial AR(1) Nikkei Series

The AR(1) process is used to detect whether the results from the SMA rules are caused by daily autocorrelations in the series. If the returns are positively auto- correlated, a higher (lower) return today will tend to be followed by a higher (lower) return on the following day; if the returns are negatively autocorrelated, a higher (lower) return today will tend to be followed by a lower (higher) return on the following day. The parameter estimates for the AR(1) process in Table 2 indicate some degree of positive autocorrelation for 1971-1990 (where $\hat{\beta}$ = 0.067763) and some degree of negative autocorrelation for 1991-2010 (where $\hat{\beta}$ = -0.026018).

Table 5 shows the daily returns from the eight SMA rules based on the artificial Nikkei price series generated from the AR(1) process for the two sub-periods. For 1971-1990, four SMA rules for buy and seven SMA rules for sell result in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals. For 1991-2010, none of the eight SMA rules for both buy and sell results in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals. In comparison, daily returns computed from the actual Nikkei series appear more likely to have been generated from the AR(1) process for the 1971-1990 sub-period than for the 1991-2010 sub-period. Given the fact that the stock market has become more efficient as a result of the reforms implemented since the 1990s, it is not surprising that the dynamics of the Nikkei exhibited no obvious sign of autocorrelation over the second sub-period.

C. Results based on Artificial GARCH(1,1) Nikkei Series

The GARCH(1,1) process allows the conditional variance to be dependent on one previous variance and one lagged squared error. Table 6 shows the daily returns from the eight SMA rules based on the artificial Nikkei price series generated from the GARCH(1,1) process. For 1971-1990, two SMA rules for buy and six SMA rules for sell result in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals. For 1991-2010, only one SMA rule for buy but three SMA rules for sell result in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals. In comparison, daily returns computed from the actual Nikkei series appear more likely to have been generated from the GARCH(1,1) process for the first sub-period than for the second sub-period.

D. Results based on Artificial GARCH(1,1)-M Nikkei Series

Finance theory claims that investors should be rewarded a higher return for bearing additional risk. The GARCH(1,1)-M process is designed to model such a phenomenon, where the conditional variance of asset returns is included in the return equation (see equation (6)). Table 7 shows the daily returns from the eight SMA rules based on the artificial Nikkei price series generated from the GARCH(1,1)-M process. For 1971-1990, five SMA rules for buy and all eight SMA rules for sell result in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals. For 1991-2010, four SMA rules for buy and six SMA rules for sell result in the daily returns computed from the actual Nikkei series lying within their respective 95% intervals. Of the four random processes, the GARCH(1,1)-M process appears to have generated daily returns that are most likely in agreement with those from the actual Nikkei series.

V. Conclusion and Implication

This study aims to find out whether or not returns from the Nikkei are agreeable with those generated from four widely used random processes for stock prices. Given the fact that we have only one sample of any time series data, the motivation of this study is to use the bootstrap to deal with this one-sample problem To proceed, we use the bootstrap to generate 2,000 artificial Nikkei series for each process and compute the return from the SMA trading rule for each of these 2,000 artificial Nikkei series. Then, we set up a 95% bootstrap percentile interval with these 2,000 returns and determine if the interval contains the return computed from the actual Nikkei series. If it does, we claim that this return agrees with those generated from the artificial Nikkei series and, moreover, we infer that the actual Nikkei series is in agreement with those artificial Nikkei series generated for a given process. Our empirical results indicate that, of the four random processes, GARCH(1,1)-M generates returns that are most agreeable with those computed from the actual Nikkei series.

Given the importance of the Japanese stock market in the world, a better grasp of the dynamics of the Nikkei is indispensable for appropriately handling Japanese stock market risk and correctly pricing Nikkei-related derivatives. A relevant case in point is the Nikkei 225 index options, which are actively traded on the Osaka Securities Exchange and the Singapore Exchange. Given our results that both the random walk with a drift[13] and the GARCH(1,1) process[14] are inadequate for depicting the Nikkei return series, an important implication of this study is that a more appropriate model for pricing Nikkei 225 index options is one that uses the GARCH(1,1)-M process to characterize the dynamics of the Nikkei return series.

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[13] The continuous-time analog of the random walk with drift in equation (3) is the arithmetic Brownian motion, which means that the Nikkei price process in equation (1) is a geometric Brownian motion (GBM). Our results imply that the well-known Black-Scholes option pricing model (1973), which assumes a GBM for the price process, is not appropriate for pricing Nikkei 225 options.

[14] Our results also imply that the GARCH option pricing model of Duan (1995) is not appropriate for pricing Nikkei 225 options.

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Figure 1. The Nikkei 225 (1971~2010)

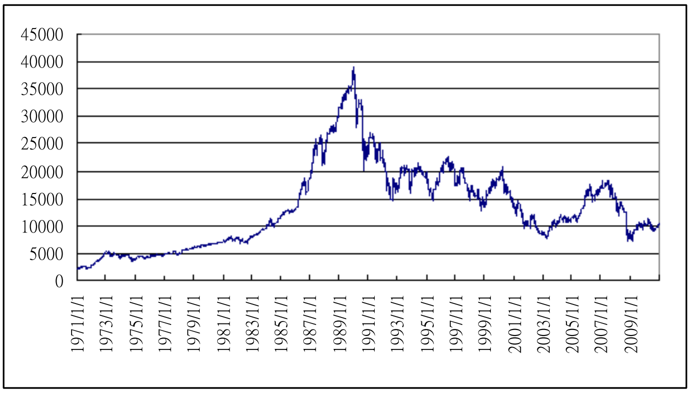

Table 1. Summary Statistics for Daily Returns on Actual Nikkei Series

	1971~1990	1991~2010
Number of Observations	5216	5218
Average Daily Return	0.0004765	-0.0001622
Daily Standard Deviation	0.0095570	0.0149640
Estimated autocorrelations:		
Lag 1	0.0677626**	-0.0304860**
Lag 2	-0.0313830**	-0.0260185*
Lag 3	0.0281386**	-0.0156630*
Lag 4	0.0167068*	0.0172377*
Lag 5	-0.0358798**	0.0090869

Note: Numbers with * (**) are significant at 5% (1%) level for a two-tailed test.

Table 2. Parameter Estimates for the Four Return-Generating Processes

Process	Parameter	1971~1990	1991~2010
RW(α)	α	0.000476 (3.600602)	-0.000162 (-0.783156)
AR(1)	α	0.000443 (3.349675)	-0.000166 (-0.803687)
	β	0.067763 (4.904032)	-0.026018 (-1.879563)
GARCH(1,1)	α	0.000751 (9.957268)	0.000217 (1.302386)
	α	0.000004 (13.961022)	0.000006 (13.080353)
	b	0.249507 (51.425821)	0.091968 (18.131580)
	c	0.735724 (109.983566)	0.883582 (160.655928)
GARCH(1,1)-M	α	0.000465 (4.422786)	-0.000142 (-0.479947)
	β	5.986531 (3.696003)	2.275804 (1.445502)
	α	0.000004 (13.928221)	0.000006 (13.141153)
	b	0.254673 (51.077408)	0.091867 (17.905101)
	c	0.728595 (104.549803)	0.883374 (158.496557)

Note: Parameters are estimated using RATS. Numbers in parentheses are standard t-ratios.

Table 3. Daily Returns from Simple Moving Average Rules based on Actual Nikkei Series

Rule	1971~1990		1991~2010	
	Buy	Sell	Buy	Sell
(1, 20, 0%)	0.000613	-0.000217	0.000062	0.000383
(1, 50, 0%)	0.000613	-0.000117	0.000167	0.000520
(1,100,0%)	0.000589	-0.000068	0.000158	0.000492
(1,200,0%)	0.000545	-0.000149	0.000329	0.000591
(1, 20, 1%)	0.000752	-0.000020	0.000234	0.000348
(1, 50, 1%)	0.000634	-0.000094	0.000230	0.000235
(1,100,1%)	0.000630	-0.000081	0.000080	0.000532
(1,200,1%)	0.000551	-0.000102	0.000264	0.000495
Average	0.000616	-0.000106	0.000191	0.000449

Note: Simple Moving Average rules are identified as (short, long, band), where short and long are the lengths of short and long moving averages respectively, and band is the percentage difference required to generate a buy or sell signal.

Table 4. Daily Returns from Simple Moving Average Rules based on Artificial RW(α) Nikkei Series

Rule		1971~1990 Buy	1971~1990 Sell	1991~2010 Buy	1991~2010 Sell
(1, 20, 0%)	Mean	0.000173	-0.000319	0.000198	0.000584
	$R_{(51)}$	-0.000039	-0.000507	-0.000034	0.000357
	$R_{(1950)}$	0.000404	-0.000084	0.000447	0.000852
(1, 50, 0%)	Mean	0.000243	-0.000260	-0.000132	0.000295
	$R_{(51)}$	0.000035	-0.000452	-0.000350	0.000042
	$R_{(1950)}$	0.000467	-0.000041	0.000171	0.000583
(1,100,0%)	Mean	0.000247	-0.000288	-0.000238	0.000230
	$R_{(51)}$	0.000042	-0.000512	-0.000454	0.000007
	$R_{(1950)}$	0.000481	-0.000066	0.000005	0.000495
(1,200,0%)	Mean	0.000148	-0.000466	-0.000524	0.000097
	$R_{(51)}$	-0.000063	-0.000659	-0.000776	-0.000239
	$R_{(1950)}$	0.000397	-0.000232	-0.000269	0.000343
(1, 20, 1%)	Mean	0.000149	-0.000306	0.000281	0.000456
	$R_{(51)}$	-0.000025	-0.000514	0.000042	0.000234
	$R_{(1950)}$	0.000364	-0.000071	0.000527	0.000711
(1, 50, 1%)	Mean	0.000323	-0.000317	-0.000153	0.000243
	$R_{(51)}$	0.000115	-0.000530	-0.000394	0.000013
	$R_{(1950)}$	0.000560	-0.000096	0.000101	0.000488
(1,100,1%)	Mean	0.000211	-0.000448	-0.000099	0.000123
	$R_{(51)}$	0.000008	-0.000654	-0.000334	-0.000094
	$R_{(1950)}$	0.000439	-0.000216	0.000173	0.000372
(1,200,1%)	Mean	0.000124	-0.000472	-0.000322	0.000085
	$R_{(51)}$	-0.000037	-0.000678	-0.000554	-0.000144
	$R_{(1950)}$	0.000352	-0.000256	-0.000062	0.000334
Average		0.000202	-0.000360	-0.000124	0.000264

Note: Simple Moving Average rules are identified as (short, long, band), where short and long are the lengths of short and long moving averages respectively, and band is the percentage difference required to generate a buy or sell signal. Mean is the average value of the 2,000 daily returns. $R_{(51)}$ and $R_{(1950)}$ are the 2.5th and 97.5th percentiles of the 2,000 returns for buy and for sell. Shaded $R_{(51)}$ and $R_{(1950)}$ are the 95% bootstrap intervals that contain the daily return from the actual Nikkei series.

Table 5. Daily Returns from Simple Moving Average Rules based on Artificial AR(1) Nikkei Series

Rule		1971~1990 Buy	1971~1990 Sell	1991~2010 Buy	1991~2010 Sell
(1, 20, 0%)	Mean	0.000362	-0.000146	-0.000270	-0.000326
	$R_{(51)}$	0.000174	-0.000330	-0.000484	-0.000530
	$R_{(1950)}$	0.000583	0.000055	0.000042	-0.000103
(1, 50, 0%)	Mean	0.000426	-0.000056	-0.000273	-0.000347
	$R_{(51)}$	0.000233	-0.000242	-0.000499	-0.000562
	$R_{(1950)}$	0.000637	0.000169	0.000027	-0.000111
(1,100,0%)	Mean	0.000342	-0.000183	-0.000262	-0.000344
	$R_{(51)}$	0.000154	-0.000379	-0.000494	-0.000553
	$R_{(1950)}$	0.000570	0.000017	-0.000035	-0.000121
(1,200,0%)	Mean	0.000488	0.000069	-0.000094	-0.000170
	$R_{(51)}$	0.000304	-0.000143	-0.000320	-0.000384
	$R_{(1950)}$	0.000711	0.000280	0.000122	0.000052
(1, 20, 1%)	Mean	0.000380	-0.000226	-0.000084	-0.000749
	$R_{(51)}$	0.000191	-0.000404	-0.000308	-0.000953
	$R_{(1950)}$	0.000592	-0.000003	0.000193	-0.000504
(1, 50, 1%)	Mean	0.000390	-0.000169	-0.000213	-0.000286
	$R_{(51)}$	0.000204	-0.000346	-0.000438	-0.000501
	$R_{(1950)}$	0.000618	0.000052	0.000041	-0.000046
(1,100,1%)	Mean	0.000441	-0.000070	-0.000340	-0.000312
	$R_{(51)}$	0.000237	-0.000261	-0.000554	-0.000530
	$R_{(1950)}$	0.000653	0.000168	-0.000107	-0.000085
(1,200,1%)	Mean	0.000516	-0.000015	-0.000194	-0.000250
	$R_{(51)}$	0.000334	-0.000204	-0.000414	-0.000484
	$R_{(1950)}$	0.000747	0.000220	0.000023	-0.000019
Average		0.000418	-0.000099	-0.000216	-0.000348

Note: Simple Moving Average rules are identified as (short, long, band), where short and long are the lengths of short and long moving averages respectively, and band is the percentage difference required to generate a buy or sell signal. Mean is the average value of the 2,000 daily returns. $R_{(51)}$ and $R_{(1950)}$ are the 2.5th and 97.5th percentiles of the 2,000 returns for buy and for sell. Shaded $R_{(51)}$ and $R_{(1950)}$ are the 95% bootstrap intervals that contain the daily return from the actual Nikkei series.

Table 6. Daily Returns from Simple Moving Average Rules based on Artificial GARCH(1,1) Nikkei Series

Rule		1971~1990 Buy	1971~1990 Sell	1991~2010 Buy	1991~2010 Sell
(1, 20, 0%)	Mean	0.000223	-0.000102	-0.000158	0.000233
	$R_{(51)}$	0.000044	-0.000288	-0.000331	0.000051
	$R_{(1950)}$	0.000437	0.000115	0.000040	0.000416
(1, 50, 0%)	Mean	0.000304	-0.000087	-0.000203	0.000179
	$R_{(51)}$	0.000140	-0.000242	-0.000378	0.000015
	$R_{(1950)}$	0.000487	0.000115	-0.000025	0.000377
(1,100,0%)	Mean	0.000430	-0.000223	-0.000129	0.000241
	$R_{(51)}$	0.000264	-0.000397	-0.000304	0.000055
	$R_{(1950)}$	0.000611	-0.000031	0.000061	0.000423
(1,200,0%)	Mean	0.000258	-0.000257	-0.000073	0.000283
	$R_{(51)}$	0.000092	-0.000404	-0.000269	0.000115
	$R_{(1950)}$	0.000445	-0.000063	0.000126	0.000493
(1, 20, 1%)	Mean	0.000377	-0.000170	-0.000070	0.000260
	$R_{(51)}$	0.000190	-0.000348	-0.000252	0.000084
	$R_{(1950)}$	0.000568	0.000012	0.000146	0.000469
(1, 50, 1%)	Mean	0.000396	-0.000121	-0.000153	0.000247
	$R_{(51)}$	0.000224	-0.000297	-0.000333	0.000074
	$R_{(1950)}$	0.000616	0.000089	0.000037	0.000428
(1,100,1%)	Mean	0.000424	-0.000288	-0.000098	0.000178
	$R_{(51)}$	0.000255	-0.000443	-0.000274	0.000019
	$R_{(1950)}$	0.000608	-0.000115	0.000102	0.000372
(1,200,1%)	Mean	0.000395	-0.000340	-0.000133	0.000250
	$R_{(51)}$	0.000216	-0.000508	-0.000317	0.000076
	$R_{(1950)}$	0.000593	-0.000135	0.000045	0.000432
Average		0.000351	-0.000199	-0.000127	0.000234

Note: Simple Moving Average rules are identified as (short, long, band), where short and long are the lengths of short and long moving averages respectively, and band is the percentage difference required to generate a buy or sell signal. Mean is the average value of the 2,000 daily returns. $R_{(51)}$ and $R_{(1950)}$ are the 2.5th and 97.5th percentiles of the 2,000 returns for buy and for sell. Shaded $R_{(51)}$ and $R_{(1950)}$ are the 95% bootstrap intervals that contain the daily return from the actual Nikkei series.

Table 7. Daily Returns from Simple Moving Average Rules based on Artificial GARCH(1,1)-M Nikkei Series

Rule		1971~1990		1991~2010	
		Buy	Sell	Buy	Sell
(1, 20, 0%)	Mean	0.000261	-0.000159	-0.000101	0.000253
	$R_{(51)}$	0.000087	-0.000344	-0.000288	0.000075
	$R_{(1950)}$	0.000452	0.000041	0.000073	0.000433
(1, 50, 0%)	Mean	0.000285	-0.000142	-0.000235	0.000264
	$R_{(51)}$	0.000103	-0.000329	-0.000413	0.000071
	$R_{(1950)}$	0.000476	0.000057	-0.000046	0.000457
(1,100,0%)	Mean	0.000407	-0.000183	-0.000016	0.000312
	$R_{(51)}$	0.000215	-0.000360	-0.000190	0.000126
	$R_{(1950)}$	0.000598	0.000016	0.000182	0.000502
(1,200,0%)	Mean	0.000374	-0.000279	0.000022	0.000431
	$R_{(51)}$	0.000190	-0.000453	-0.000161	0.000244
	$R_{(1950)}$	0.000564	-0.000088	0.000219	0.000637
(1, 20, 1%)	Mean	0.000336	-0.000193	0.000085	0.000187
	$R_{(51)}$	0.000168	-0.000365	-0.000102	0.000018
	$R_{(1950)}$	0.000533	0.000013	0.000266	0.000365
(1, 50, 1%)	Mean	0.000463	-0.000177	-0.000089	0.000371
	$R_{(51)}$	0.000270	-0.000354	-0.000263	0.000188
	$R_{(1950)}$	0.000669	0.000032	0.000101	0.000562
(1,100,1%)	Mean	0.000488	-0.000220	-0.000114	0.000266
	$R_{(51)}$	0.000311	-0.000404	-0.000295	0.000090
	$R_{(1950)}$	0.000665	-0.000038	0.000097	0.000471
(1,200,1%)	Mean	0.000456	-0.000276	-0.000056	0.000328
	$R_{(51)}$	0.000277	-0.000451	-0.000243	0.000136
	$R_{(1950)}$	0.000640	-0.000082	0.000139	0.000519
Average		0.000384	-0.000204	-0.000063	0.000302

Note: Simple Moving Average rules are identified as (short, long, band), where short and long are the lengths of short and long moving averages respectively, and band is the percentage difference required to generate a buy or sell signal. Mean is the average value of the 2,000 daily returns. $R_{(51)}$ and $R_{(1950)}$ are the 2.5th and 97.5th percentiles of the 2,000 returns for buy and for sell. Shaded $R_{(51)}$ and $R_{(1950)}$ are the 95% bootstrap intervals that contain the daily return from the actual Nikkei series.