TEST OF GLOBAL MARKET EFFICIENCY, THROUGH MOMENTUM, OSCILLATION, AND RELATIVE STRENGTH INDEX STRATEGIES

by

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Bachelor of Business Administration
Simon Fraser University, 2003

PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF ARTS

In the
Department
of
Economics

SIMON FRASER UNIVERSITY

Fall 2004

APPROVAL

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Degree:	**M. A. (Economics)**
Title of Project:	**Test Of Global Market Efficiency, Through Momentum, Oscillation, And Relative Strength Index Strategies**

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SIMON FRASER UNIVERSITY

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ABSTRACT

This paper tests the weak-form global market efficiency, by comparing the returns of technical trading strategies to the returns of buy-and-hold strategies on 24 country indexes and 1 world index. The technical trading strategies examined in this paper include static and dynamic momentum approaches, oscillation strategy, and Relative Strength Index strategy. Empirical testing suggests that it is possible for the trading strategies to significantly outperform the buy-and-hold strategy in some country indexes and even the world index. However, no excessive profits are extracted in United States and Germany from all the technical trading strategies, noting that these countries are weak-form efficient in the context of this paper. Furthermore, the technical trading strategies do not work well during extreme expansionary periods, but they are useful in filtering losses during recessionary periods.

ACKNOWLEDGEMENTS

First of all, I want to thank Professors Geoffrey Poitras and Robert Grauer of the Faculty of Business Administration for the tremendous support and valuable advice they have given me in this paper. They were a great influence in bringing me to business and finance; I admire them both immensely. I am also very grateful for the help of Professor Robert Jones of the Department of Economics and Professor John Heaney of the Faculty of Business Administration.

Lastly, I want to thank my family for all the love and encouragement they have given me; my friends who have always supported me; and all my students in SFU who have given me a sense of fulfillment.

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LIST OF ABBREVIATIONS

N	=	total number of observations
n	=	the n^{th} observation / each specific time
D	=	excessive profit
DD	=	daily difference of stock price
EMA	=	exponential moving average
RSI	=	relative strength index
RS	=	relative strength
MR	=	mean-reversion
MM	=	momentum
μ	=	the mean under null hypothesis
s	=	standard deviation
t	=	t-stat

Subscripts

c	=	each specific country
i	=	each specific technical trading strategy
h	=	the buy and hold strategy
n	=	the n^{th} observation / time subscribe

1 INTRODUCTION

In 1970, Fama's work called "Efficient Capital Markets: a Review of Theory and Empirical Work" created a financial field of study of market efficiency. He distinguishes financial markets into three forms of market efficiency - the strong form, the semi-strong-form, and the weak-form market efficiency. The efficient market is defined as the market where the stock prices would always "fully reflect" all available information. The weak-form market efficiency, which this paper focuses on, is more specifically defined as a situation where past prices and returns cannot predict the future price and return. In other words, the technical analysis is worthless as it is impossible to consistently extract excessive profits using the chart, the trend, the historic prices, and the statistical analysis.

Many studies were published regarding testing the weak-form market efficiency. In order to show weak-form market inefficiency, the studies have tried to uncover evidences of abnormal profits from technical analyses. Thaler (1987) approaches it through the January effect and Thaler (1987), French (1980) also examine the anomalies associated with weekend, holiday, turn of the month, and intraday effects. Some analysts employ the performance ratios like price-earning ratio, and price-to-book ratio. Some use momentum and mean-reversion strategies, which will be discussed in later sections of this paper. Chordia and Shivakumar (2002) employ the test with return predictability from macrovariables. Some of these studies show market inefficiency, but some of the evidence are mixed.

This paper in general will employ two types of technical analysis strategies: the momentum strategy and the mean-reversion strategy. The momentum anomaly will branch out into the static, semi-dynamic, and dynamic momentum strategies and also the oscillation strategy. The mean-reversion anomaly will branch out into the Relative Strength Index strategy.

The purpose of the paper is to test the global weak-form market efficiency. Twenty-four country indexes and one world index were used to test the theory. There are a total of seven technical trading strategies and 25 global indexes. A total of 175 tests of weak-form market efficiency exists. A proof of significance for these tests indicates the possibility of extracting excessive profits from technical analysis. In this 21st century of high globalization, fund managers should maximize the value of their portfolio by diversifying investment globally. The result of this paper could enhance the understanding of the market efficiency level of each country, which could be very useful in making investment decisions.

The structure of this paper begins with the overview of the momentum and the mean-reversion anomaly. Then section 3 will describe empirical approach and the methodology used to test the weak-form market efficient theory. Section 4 will describe the data, and then followed by the results of the technical trading strategies and the market efficiency. The last section, section 6, will discuss and conclude the findings of this paper.

2 OVERVIEW OF MOMENTUM AND MEAN-REVERSION

One of the earliest researchers to use ordinary least squares to estimate market return were Scholes and Williams (1977). They discovered autocorrelation in stock prices - return of last period will explain the return of current period - this is generally known as the momentum. Jegadeesh and Titman (1993) tried to exploit this anomaly to set up an investment strategy. They grouped all stocks from January 1963 to December 1989 traded on the NYSE into deciles base on the prior six-month return and compared the returns of all deciles in the next six-months. They discovered that the best prior return decile outperformed worst return decile by 10 percent on an annual basis.

DeBondt and Thaler (1985) ranked all stocks traded on the NYSE by their prior three-year cumulative return and formed a "winner" portfolio and a "loser" portfolio, each consisting of 35 best and worst return stocks. They then discovered that the average annual return of the loser portfolio is higher than the average return of the winner portfolio by about 8 percent per year. This behavior is defined as long-term mean-reversion.

The momentum and the mean-reversion behaviors contradict since one predicts a loser stock is likely to performing poorly while the other predicts it is likely to revert as a winner. The only difference between the tests lies in the length of period of return observed in forming the best or worse portfolio, which are six monthes in Jegadeesh and Titman (1993) and three years in De Bondt and Thaler (1985). It poses a question of what determines the momentum and what determines the mean-reversion.

Barberis, Shleifer, and Vishny (1998) transformed the evidence in momentum and mean-reversion into a very simple model, similar to Hong, Lim, and Stein (1999, 2000). However it contains assumption that earning moves between two "regimes": earnings are mean-reverting and earnings are trended. The transition probability of the regimes, and also the statistical properties of the earning process in each regime, are embedded in the investors' mind. In any given period, the firm's earnings are likely to stay in a given regime and investors use this information to update their beliefs about the regime they are in. Although this model does not explain the reasons, it blueprints the fields to explain momentum and mean-reversion.

2.1 Explanations of Momentum

First, some researchers attribute momentum behaviour to data snooping. Boudoukh, Richardson, and Whitelaw (1994) view the autocorrelation in the return as a result of measurement error, and has nothing to do with the fundamentals. The measurement errors include non-synchronous trades and price discreteness. They also suggest that the momentum could be a result of off-market trade and trade mechanisms in different market structures. However, Conrad and Kaul (1989) showed that autocorrelation cannot be the result of market error and non-synchronous trading.

Opposing view of Boudoukh, Richardson, and Whitelaw (1994) describe the market as inefficient and generated a list of possible explanations. Watkins (2002) attributes the consistency in stock returns to information diffusion. Hong, Lim, and Stein (2000) built a model to explain the momentum behavior in stock prices. They created a world of two types of agents: "newswatcher" and "momentum traders." Each type of agent is only able to "process" some subset of the available public information.

The newswatchers make forecasts based on their private signals about future fundamentals and the momentum traders forecast prices conditional on past price changes. In this world, to possibly reflect the real market, private information diffuses gradually across the newswatcher population. Only when newswatchers are actively looking after the prices do prices adjust slowly to new information. This comes momentum, caused by inadequate information diffusion or underreaction. This theory is also supported by Grinblatt, Titman, and Wermer (1995) and Boudoukh, Richardson, and Whitelaw (1994).

Watkin (2002) also attributes the cause of momentum to discount rates. A better explanatory model is from Berk, Green, and Naik (1999). They compute the firm's value based on the net cash flow. Cash flow at each period will be the sum of cash flow from all of the projects from the firm. Risky projects and conservative projects exist, but they are discounted by the same discount rate. As likely in the short-term that the firm invests in new projects that have similar risk structure and that there is no default in cash flow, the return in stock will reflect the discount rate. It creates persistence in the trend of stock price.

Lo and MacKinlay (1988) suggest the cause of the positive autocorrelation, or momentum effect, to be infrequent trading. They point out that small capitalization stocks trade less frequently than large stocks. When common factors affect the whole market, information injects faster into large capitalization stock price and slowly strew to the small stock. As result, serial correlation appears in the stock price. Those common factors could be dividend yield, default spread, yield on three month t-bill, and term structure spread as mentioned in Chordia and Shivakumar (2002).

Jegadeesh and Titman (1993) argue that the anomaly should not be attributed to delayed stock price reactions to common factors. Instead they state that the delay in price reactions is a result of firm-specific information. This belief is also supported by Conrad and Kaul (1998). On a more macro level, Grinblatt and Moskowitz (2003) claim that large portion of the firm-specific momentum can be explained by industry momentum. Further, Lakonishok (1994) looks deeply into the firm's ratios involving stock prices proxy for past performance to explain the momentum behavior.

Nevertheless, evidence in Grundy and Martin (2001) suggests momentum is not explained by time varying factors (such as common factors), cross-sectional differences (firm's specifics), or industry effects. Grundy and Martin (1998) show that the momentum should be predicted by trading volume. A study by Lee and Swaminathan (2000) discovered that past trading volume influences both the magnitude and the persistence of future price momentum. Specifically, high (low) volume winners (losers) experience fast momentum reversal. They then generate investment strategies conditional on past volume, and find out if past trading volume is useful to reconcile short-term "underreaction" and long-term "overreaction" effects. Aside from this, Lee and Swaminathan (2000) use the trading volume to discover more anomalies.

In addition, a significant number of the explanations for momentum falls into the field of investor psychology. One of the simple psychological explanations identified by Edwards (1968) is the "conservatism" - individuals dislike changes and slowly accept new evidence. He also points out that opinion change is very orderly, but it is insufficient in amount. This describes the situation where investor behavior slowly reflects new information in the stock prices.

Another psychological explanation is "overconfidence." Overconfidence is derived from a large body of evidence from cognitive psychological experiments and surveys which shows that individuals overestimate their own abilities. Daniel, Hirshleifer, and Subrahmanyam (1998) consider that overconfident investors give too much weight to the private signal. When public information signals arrive, investors only partially correct the price. As more public information arrives, stock prices will gradually move toward the full-information value, or the fundamental value. Furthermore, on a more advance level, as the overconfident investors observe the biased outcomes that are consistent with their expectations, they will update their confidence in a biased manner. This behavior is called "attribution theory." Daniel, Hirshleifer, and Subrahmanyam (1998) say that as public information aligns with the private signals, investors will further overreact to the preceding private signal. As result, continuous overconfidence creates persistence in overreaction that lead to momentum in prices.

Tversky and Kahneman, (1974) provide another psychological explanation as "representativeness heuristic." This theory says that a person evaluates the probability of an uncertain event, or a sample, by the degree to which it is (i) similar in its essential properties to the parent population, (ii) reflects the salient features of the process by which it is generated. To illustrate, if a company has a consistent history of return, accompanied by salient and enthusiastic descriptions of its success, investors may view that the past history is representative of return. Perhaps the returns are just from a random process with a few lucky successes; investors see "order among chaos" and conclude returns as a path from past return.

2.2 Explanations of Mean-Reversion

According to Fama and French (1987), if returns are generated by the combination of a random walk and a stationary mean-reverting process, the serial correlation of the stock price will be a U-shaped function of the holding period. The first-order autocorrelation becomes more negative as shorter holding periods lengthen, but it gradually returns to zero for longer holding periods because the random walk component dominates. The curvature of this U-shaped function depends on the relative variability of the random walk and mean-reverting components. Fama and French's (1987) parameter estimates imply that the autocorrelation coefficient is monotonically decreasing for holding periods up to three years. That is, the mean-reversion occurs at a holding period greater than or equal to three years. However, there is also short-term mean reversion as pointed out by Lo and MacKinlay (1988).

Among all the explanations, there is always a group of people who believe that mean-reversion is data mining and does not exist. Fama and French (1988a) discover that autocorrelation for 3- to 5-year returns for 1926-1985 is strongly negative. However, if the sample ranges from 1926-1940, the evidence of strong negative autocorrelation in 3- to 5-year returns disappears. Likewise, Zarowin (1989) finds no evidence that in small stocks, often losers, have higher expected returns than large stocks, often winners.

Grinblatt and Moskowitz (2003) and Jegadeesh (1990) believe that some portion of the short-term return reversals is driven by microstructure biases such as bid-ask bounce. Kaul and Nimalendram (1990) show that bid-ask errors lead to spurious volatility in transaction returns and about half of the daily return variance can be induced by the bid-ask spread. Grinblatt and Moskowitz (2003) and Lenmann (1990)

also believe that mean-reversion is a result of liquidity. Grinblatt and Moskowitz (2003) observe that some stocks are illiquid at the end of December. Overreaction will take time in January and will create mean-reversion.

A significant group of researchers believe that overreaction contributes to mean reversion. DeBondt and Thaler (1985) define overreaction as when an investor has weighted too much on past performance of a firm and the return should revert. Kahneman and Tversky (1982), using experimental psychology, notice that people tend to overreact to unexpected and dramatic events. Fama and French (1996) believe that the three-factor model can account for the overreaction evidence. Chopra, Lakonishok, and Ritter (1992) discover that overreaction effect is substantially stronger for smaller firms than for large firms. Even after adjusting for size and beta, overreaction remains.

In addition, overreaction could be a result of accumulation of underreactions. Hong and Stein (1999) state, "Every existence of underreaction sows the seeds for overreaction." Virtually, all the momentum explanations discussed in the previous section could lead to overreaction. At one unpredictable time, the stock price will mean-revert.

Another class of explanation is tax loss trading. Grinblatt and Moskowitz (2003) suggest that at the end of December, fund managers sell off losing stocks to reduce realized capital gain tax or increase tax credit. Stock selling at the end of December will create loser persistence in December and reversals in January. However their model does not explain that the winners revert because investors do not sell winning stock to reduce tax. Constantiniedes (1984) argues that the tax loss selling at the end of the year is irrelevant.

Fischer (1999) states that volatility in stock today is can be partially attributed to window dressing. Close to each quarter, fund managers try to make their funds look attractive before disclosing an updated list of investment holdings. So they will buy recent hot winners and sell their losers. This action deceives potential and current investors. Later after the disclosure, they will sell the winner and may buy back the loser, creating a short-term mean-reversion.

Several researchers explain the mean-reversion with risk structure. Recall the net cash flow model in the momentum section: a firm's value depends on a sequence of cash flows discounted by a risk factor. Berk, Green, and Naik (1999) suggest that as the firm loses a particularly low-risk project, the average risk will rise. The firm's value will drop suddenly from the net cash flow method valuation. This theory is supported by DeBondt and Tthaler (1987). Also, Chan (1998) finds empirical evidence supporting this theory - losers' betas increase after a period of abnormal loss and winners' betas decrease after a period of abnormal gain. Chan's strategy of buying high betas and selling low betas generates excess return. Nonetheless, he points out that the return is likely to the compensation of high risky strategy.

Lehmann (1990) attributes the mean-reversion to difference in size of the firm. Although he found out the losers outperform winners by 16.6%, when poor earners are matched with winners of equal size, there is little difference in the return.

Lee and Swaminathan (2000) look at the mean-reversion and momentum behaviors to the volume traded. They find low volume stock outperform high volume stock. Among winners, low volume stocks show greater persistence in price momentum. Among losers, high volume stocks show greater persistence in price

momentum. In addition, low volume stocks are commonly associated with value stocks. High volume stocks are commonly associated with glamour stocks. Mean-reversion likely appears as stocks reach extreme high volume and extreme low volume.

3 METHODOLOGY AND EMPIRICAL APPROACH

Under the weak-market efficiency hypothesis, no excessive returns could be extracted from technical analysis. This paper, in an attempt to reject this hypothesis, will form a total of seven technical trading strategies and examine the returns of these strategies over the simply buy and hold strategy. The design of this test is the Matched Pairs t Procedure or, intuitively, the mean difference test.

Each year in the data of daily global price indexes, seven returns of the technical trading strategies and one return of the buy and hold strategy will be generated. The number of years in the price index data will be the number of observations, "N." The annual return of each technical trading strategy is denoted "R_{cin}" where subscript "c" represents the country, "i" represents one of the seven technical trading strategies, and "n" represents the n^{th} year or the time series of the observation. Similarly, the annual return of the buy and hold strategy is denoted "R_{chn}". As result, the difference or the excessive return will be "R_{cin} - R_{chn}", or denoted "D_{cin}". The Matched Pairs t statistic is therefore:

$$t_i = \frac{\overline{D}_i - \mu_i}{s_i / \sqrt{N}}, \quad \text{(Moore 1995. p419)}$$

in which $\overline{D}_i$ is the mean of "D_{cin}" and "s_i" is the sample standard deviation of "D_{cin}".

Under the null hypothesis that the excessive return is zero, or μ_i =0, the Matched Pairs t statistic will be:

$$t_i = \frac{\overline{D}_i}{s_i / \sqrt{N}}.$$

The test is designed to be one-tailed as this paper focuses on the possibility of over-performing the buy and hold strategy. A significant rejection of the null hypothesis indicates that the typical technical trading strategy makes it possible to extract excessive profits out of the normal buy and hold strategy; therefore, the market is not weak-form efficient. In contrast, a failure to reject the hypothesis indicates there is not enough evidence to prove that the market is weak-form inefficient.

Under this type of efficient market testing, the necessity of the market rate and the risk free rate is not required. This method avoids the problem of selecting the market proxy as mentioned in Roll's (1978) critique. The next section will outline the seven technical strategies: 3-day static momentum strategy, 6-day static momentum strategy, 12-day static momentum strategy, semi-dynamic momentum strategy, dynamic momentum strategy, oscillation strategy, and the relative strength index strategy. Several assumptions and actions apply to all seven strategies:

(1) All the technical trading strategies employ *ex ante* variables, so the buying and selling signals can realistically serve as the forecasts of the future price movement based on the past price performance.

(2) To avoid time lag, the buy and sell actions are implemented immediately when the signals appear. Realistically, if the reference price is the close price, the confirmation of the signal takes time 1 minute before the close, and the actual buy action is executed at the last minute. This action is superior to the buy/sell at the open price as the price difference between the close and the next open could be substantially large.

(3) The distribution of the security return is assumed to be log-normal; and the daily security difference is assumed to be normally distributed.

3.1 Static Momentum Strategy

As the name suggests, static momentum strategies stem from the momentum anomaly. It is based on the belief that the price persists over time. All of the static momentum strategies in this paper embed the following four propositions:

(1) The word "static" describes the circumstance that the buy signals and the sell signals do not respond to the qualitative price movements. The static momentum strategy is based on the belief that stock price movements are persistent in the "direction" of the change, and not in the "performance" of the price change.

(2) The number "n" in the "n-day static momentum strategy" refers to the observation period. This strategy supposes that the buy signals appear when at least 67% of the observation days' returns are positive. For instance, in the 3-day static momentum strategy, the buy signals appear when at least 2 days' returns out of 3 days are positive.

As a result, two initiative buy signal are generated at "n" when (n-2, n-1,n) is (-,+,+) and (+,-,+).

(3) The holding period for each buy signal is 3 days.

(4) Continual update of the buy signals applies. Take an example when the return for the past 9 periods (n-8,n-7,n-6,n-5,n-4,n-3,n-2,n-1,n) is (-,-,+,+,+,+,-,-,+); if the observation period is 6 days, then the initial buy action will take time at the close of "n-3" and hold until the end at "n". Nevertheless, the buy signal is still active at "n," as the returns of 4 days out of 6 are positive, the hold will continue at "n" until the signal is off at "n+3", "n+6", etc.

3.1.1 3-Day Static Momentum Strategy

The 3-day static momentum stresses the belief that momentum occurs in the fairly short term, around a week. This strategy will automatically buy the stock when the past return at (n-2,n-1,n) is (-,+,+) and (+,-,+); and will continue to hold when the return is (+,+,-).

3.1.2 6-Day Static Momentum Strategy

The 6-day static momentum, compared to the 3-day one, is a bit conservative and requires 6 days of observation before entering a trade. The buy actions take place when at least 4 days' returns out of 6 days are positive. The holding period is still 3 days. As result, the trade frequency will be smaller.

3.1.3 12-Day Static Momentum Strategy

The 12-day static momentum, compared to the other two, is the most conservative as it searches for signs in the past 12 days and holds the security for only 3 days. The buy actions take place when at least 8 days' returns out of 12 days are positive.

3.2 Semi-Dynamic Momentum Strategy

One of the salient shortcomings of the pure static strategy is the lack of consideration of the performance measure. The semi-dynamic momentum strategy eliminates this deficiency by implementing magnitude-sensitive buy signals. It is "dynamic" as the buy signals can change. However, the holding period remains 3 days, so it is semi-dynamic.

The buy signals are formed through statistical process. In general, the buy signal is generated when:

$$DD_{cn} \geq \mu_{cn} + t^{*}_{1-\alpha,N-1,1} \times S_{cn}/\sqrt{N} ,$$

in which "DD_{cn}" is the daily difference of the security price of country "c" at time "n"; "N" is the number of observation days; "μ_{cn}" is the mean of the DD_{cn} for the past "N" observation days; "$S_{cn}/\sqrt{N}$" is the standard error of the DD_{cn} for the past "N" observation days; and "$t^{*}_{1-\alpha,N-1,1}$" is the critical t value for 1-alpha confident, N-1 degrees of freedom, and one-tailed test. As the general model of buy signal is formed, the next step will be to quantify the variables used in the paper:

(1) The DD_{cn} will be the security price at "n" minus the security price at "n-1".

(2) The number of observation days, "N", is set to be 20. It is an arbitrary number. If "N" becomes larger, then the mean and standard error of the DD_{cn} become stable. If "N" becomes smaller, the mean and standard error of the DD_{cn} will be volatile, adding risk to the buy signals.

(3) The "μ_{cn}"and "$S_{cn}/\sqrt{N}$" keep updating as newly security price change joins the calculation and the 21st past observation fade out.

(4) An arbitrary critical p-value (or 1- alpha) of 90% is set. Then we can generate the critical value of t, "$t^*_{0.10,19,1}$" to be 1.34.

Overall, to interpret the formula, if DD_{cn} is greater than $\mu_{cn} + 1.34 \times S_{cn}/\sqrt{20}$, then the probability of observing that typical DD_{cn} will be at least 90%. This indicates that security price change is significantly large, a signal that the price moment is in an upward trend, so it is the right time to buy the security.

3.3 Dynamic Momentum Strategy

Although the semi-dynamic strategy is better than the pure static one, there is a major pitfall in the selling of the security. Because the "μ" keeps updating with the new price difference, a buy signal, indicating a significant price increase, will raise the "μ". After the stock is sold on the third day, a continual buy signal and the next buy signal would require a greater price increase. Therefore, a successful buy will contest the next buy action.

The dynamic momentum strategy goes one step further than the semi-dynamic strategy as, in addition to the buy signals, the sell signals are also determined by the

security performance. It is fully dynamic as both the buy signals and sell signals can change. The buy signals are exactly identical to the buy signal of the semi-dynamic strategy. On the other hand, the sell signals are triggered when:

$$DD_{cn} \leq \mu_{cn} + t^*_{\alpha,N-1,1} \times S_{cn}/\sqrt{N},$$

The formula and the notations are the same as in the semi-dynamic strategy buy signal, except the inequality sign and the critical p-value. In this paper, an arbitrary critical p-value (or alpha) of 16% is used. Then the critical value of t, "$t^*_{0.16,19,1}$" will be -1.00.

The overall interpretation will be that if daily difference of the security price is smaller than $\mu_{cn} - 1.00 \times S_{cn}/\sqrt{20}$ (or price loss is greater than $\mu_{cn} - 1.00 \times S_{cn}/\sqrt{20}$ in absolute term), then the probability of observing that typical DD_{cn} will be at most 16%. This indicates that security price change is significantly small (the price loss is significantly large), a signal that the price upward moment ends, so it is the right time to sell the security.

3.4 Oscillation Strategy

According to Poitras (2005) "the term oscillator refers to a wide range of techniques that can be based on substantively different calculations and motivations. The unifying notion connecting the techniques is that the chart pattern calculated from the original price chart oscillates or fluctuates within a defined range."

This paper will focus on the narrow definition found at www.futuresource.com (2004) which defines an oscillator as "the simple difference between two moving averages". A specific form is the dual exponential moving average. Generally, two

different periods of exponential moving average (EMA) are formed: a slow EMA will cover a longer period, where price changes dilute slowly in the EMA; a fast EMA will cover a shorter period, so price changes incorporate faster in the EMA. When the fast EMA accelerates away the slower EMA, or when the difference of fast EMA and the slow EMA is positive, the security is described to be gaining momentum in the upward trend. When the fast EMA drops below the slower EMA, or when the difference of fast EMA and the slow EMA is negative, the security is described to show bearish trend. According to Schwager (1996, p.556): "Oscillators perform well when a market is in a trading range – that is, a sideways trend. They work poorly, however, when a market is in a strong uptrend or downtrend."

The oscillation strategy in this paper employs the 5-day EMA as the fast EMA and the 20-day EMA as the slow EMA. The formula of the EMA suggested by Kaufman (1978) is:

$$EMA_n = \frac{1P_n + aP_{n-1} + a^2 P_{n-2} + \ldots + a^{N-1} P_{n-N+1}}{1 + a + a^2 + \ldots + a^{N-1}}$$

where P_n is the security price at "n" and "a" is set to be 0.5 in this paper. The use of the exponential is to put more weight on the recent price and less weight on the relatively historic price. The buy signals appear if the difference of the 5-day EMA and the 20-day EMA is positive. The sell signals appear when the difference is negative.

3.5 Relative Strength Index Strategy

The relative strength index (RSI) strategy can be used as both a momentum strategy and the mean-reversion strategy. It depends on the interpretation of the over-bought and the over-sold levels. For instance, the over-sold signals could be interpreted

as a situation where the security price is below its fundamental value and is expected to go back to the fundamental level. On the other hand, the over-sold signals could be a signal of subsequent price fall. This paper will interpret the RSI as the mean-reversion strategy. Nevertheless, as the returns in this paper are expressed as log return, multiplying the RSI returns by a factor of negative one could shift the results from mean-reversion strategy to momentum strategy[1].

According to Schwager (1996, p542), "RSI compares the relative strength of price gains on days that close above the previous day's close to price losses on days that close below the previous day's close." The process of calculating the relative strength index is detailed as follows:

(1) The RSI can be constructed with any number of observation days; a 9-day period is used in this paper. A shorter observation period induces faster and a more sensitive indicator, and *vice versa.*

(2) An up average is formed by adding all the prices gained on the up days of the 9-day period and dividing the total by nine.

(3) A down average is formed by adding all the absolute values of the prices lost on the down days of the 9-day period and dividing the total by nine.

(4) A relative strength (RS) can be calculated by dividing the up average by the down average.

(5) The following formula will lead to the RSI:

$$RSI = 100 - \left[100 / (1 + RS) \right]$$

[1] Substantial difference may occur as the alternative strategy would involve short-selling.

An over-sold signal occurs when the RSI is very small. As down average dominates the up average, 0<RS<1, so RSI will be smaller than 50. Inversely, an over-bought signal will result in a high RSI, 50<RSI<100. Since we interpret the RSI strategy as a mean-reversion strategy, the over-sold signals will be the buy signals and the over-bought signals will be the sell signals. The over-sold signals usually range from 20 to 30 and the over-bought signals usually range form 70 to 80. This paper will arbitrarily pick the combination of (20, 80) respectively.

4 DATA

As we are now in the high cross-border investment era, global market efficiency becomes more important. "If momentum exists globally, then a strategy that actively allocates funds from loser to winner markets might be more attractive than a globally diversified buy-and-hold strategy (Fong, Wong, and Lean, 2003)." This paper will examine the global weak-form market efficiency by testing the technical strategy return of 24 country indexes and 1 world index from the Morgan Stanley Capital International (MSCI) World Index. The 24 country indexes consist of Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Indonesia, Italy, Japan, Korea, Malaysia, Netherlands, Norway, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, United Kingdom, and United States. All data are sourced from Datastream.

"The MSCI World Index is a free float-adjusted market capitalization index that is designed to measure global developed market equity performance (MSCI 2004)."

Every MSCI index comprises large capitalization stocks and actively traded stocks, so the problems associated with illiquidity, bid-ask spreads, and non-synchronous trading biases are eliminated. Local prices are used in the indexes, thus returns will not be distorted by the exchange rate fluctuations.

The price indexes are listed daily and the sample ranges from January 1989 to September 2004. Since only the daily closed price was provided, the daily return is formulated by comparing today's close price to that of the previous day. Due to the limitation of the data, a trade, following a signal, is assumed to be executed the moment before the close. An important assumption would be that there is no time lapse between the signal and the trade action.

5 RESULTS AND SUMMARY

5.1 Full Period Returns of the Technical Trade Strategies

Table 1 in Appendix reports the performance of all the technical trade strategies and the buy and hold strategy for all the indexes through the whole 15 years sample period. All the returns are calculated in log form and expressed annually.

5.1.1 The 3 Static Momentum Strategies

Of all the technical trading strategies, those 3 static momentum strategies are comparable because their basics are the same and they only differ in the observation period. Among them, the most successful is the 3-day observation; it over-performs the buy and hold strategy for 15 out of 25 world indexes. There are only 10 over-

performances in the 6-day strategy and only 8 in the 12-day strategy. Austria, Indonesia, Korea, Malaysia, Taiwan, and Thailand are the countries where all the static momentum strategies succeed in beating the buy and hold. Most of them cluster in the South East Asian region. Nevertheless, up to this point we cannot conclude that these markets are inefficient because the buy and hold strategy only compare the prices of the initial trading day and the last one. The Asia Financial Crisis could be the blame for all of the static momentum strategies over-performance relative to the buy and hold.

In addition, no salient trend is discovered in the number of observation days. Generally, as the observation period increases, the returns generally decrease, but there are lots of exceptions, so we cannot conclude any trend. However, a surprise appears in Japan as all 3 static momentum strategies result in negative returns. This could be understandable as the Japanese economy underwent suppression throughout the 1990's. Another surprise is found in the Netherlands and Spain; the returns are positive in 3-day observation and 12-day observation, but negative in the 6-day observation. The difference is quite high especially in Spain.

5.1.2 The Other 4 Technical Trading Strategies

We cannot cross-compare the semi-dynamic, the dynamic, the oscillation, and the RSI strategies. However, we can generally describe their performance. Of all 7 strategies, the most successful one is the dynamic strategy as it over-performs the buy and hold for 23 country indexes and 1 world index. The only exception is United States (Please refer to table 2 in Appendix). The semi-dynamic over-performs in 16 indexes; oscillation strategy over-performs in 10 indexes. The relative strength index strategy does not over-perform in any index. The success in the dynamic strategy can be

attributed to its ability to customize the trade signals with regard to the index performance. Under the dynamic strategy, we know that the return from Japan can be positive with a more customized strategy.

Another interesting logic can be formed by comparing the semi-dynamic and the dynamic strategies: the selling signal is as important as the buy signal. A customized sell signal, as in the dynamic strategy, enhances the return in all indexes except Taiwan. We can now move onto the test result of the strategies.

5.2 Return of All the Strategies Listed Yearly

Table 3 averages all the returns across the 25 global indexes and expresses them year by year. Three distinctive observations are discovered:

(1) During the periods of negative buy and hold return, all of the technical trading strategies over-perform. It signifies that it is possible to filter the losses during a year.

(2) During the periods of moderate growth, some strategies over-perform and some under-perform. It varies strategy by strategy.

(3) During the periods of rapid growth, the technical strategies do not hammer the buy and hold strategy. The momentum in the indexes during the period is strong. An attempt to filter the anticipated losses inversely filters the gains.

In conclusion, these technical trading strategies could be employed to hedge and eliminate the negative market risk.

5.3 Test Result for the Static Momentum Strategy

5.3.1 Test Result of the 3-Day Static Momentum Strategy

Table 4 shows the result of the matched pair t statistic of the 3-day static momentum strategy. Korea, Malaysia, Singapore, and Taiwan reject the null hypothesis at 10% significance; Canada, and Thailand reject it at 5% significance; in the extreme, Indonesia rejects the weak-form efficiency hypothesis at 1% significance. Most of these countries are located in the South East Asian region. However, it is quite surprising that Canada is weak-form inefficient under this test. In contrast, Canada's neighbour, United States, shows the least excessive return. The 3-day static momentum strategy yields a loss of 9.08% compared to the buy and hold strategy. In addition, the standard error is 2.26%, one of the lowest in the data; signifying that the loss is consistent.

5.3.2 Test Result of the 6-Day Static Momentum Strategy

With the 6-day momentum strategy, only Indonesia, Korea, and Thailand are proven to be weak-form market inefficient. The Result is reported in Table 5. This time, again, the Indonesian market is proven to be weak-form inefficient. The excessive return from this strategy is 17.42%, better than that of the 3-day static momentum strategy with 30.17%. The Netherlands and United States provide the least returns, -9.70% and -8.26% respectively.

5.3.3 Test Result of the 12-Day Static Momentum Strategy

Table 6 reports the test for the 12-day static momentum strategy. None of the global markets is proven to be inefficient. Indeed, 17 out of the 25 markets show negative excessive returns anchoring the buy and hold strategy. The excessive return in

Indonesia is actually larger than that in the 6-day static momentum strategy, but the standard error is much larger. Belgium, France, Hong Kong, Switzerland, United Kingdom, and United States report the least gain (most loss), but United Kingdom is proven to be most efficient in this test.

5.4 Test Result for the Semi-Dynamic Momentum Strategy

Table 7 shows that the semi-dynamic momentum strategy beats the buy and hold strategy in 9 country indexes and in the world index. The countries are Austria, Canada, Hong Kong, Indonesia, Italy, Malaysia, Norway, South Africa, Taiwan, and Thailand. On the other hand, Switzerland and the Netherlands are proven to be efficient under this test.

5.5 Test Result for the Dynamic Momentum Strategy

The result generated from this dynamic momentum strategy can significantly separate the inefficient market from the efficient ones. The result is shown in table 8. German and United States markets are the most efficient under this test as they are the only two that produce negative excessive returns. Of the remaining 23 indexes, 14 significantly produce positive excessive return. Austria, Canada, Hong Kong, Italy, Korea, Malaysia, Norway, Singapore, South Africa, Spain, and Sweden are inefficient at 5% level. The world index, Indonesia, and Thailand are inefficient at 1% level. The excessive return in Indonesia and Thailand are 40.58% and 35.46% respectively. Although the excessive return in the world index is only 13.28%, the standard error is quite low, making it highly significant. It is surprising that Taiwan, proven to be weak-form market inefficient in the semi-dynamic strategy, appears to be efficient now.

Perhaps, the bearish sentiments in the Taiwanese market arrived promptly, leaving the sell signals ineffective in exiting the market.

5.6 Test Result for the Oscillation Strategy

Table 9 shows the test result for the oscillation strategy. Only Indonesia, Korea, Malaysia, and Thailand get significant excessive returns. Again, the Netherlands, United Kingdom, and United States are proven efficient under this test.

5.7 Test Result for the Relative Strength Index Strategy

Table 10 reports the test result for the relative strength index (RSI) strategy. If we interpret the RSI as a mean reversion indicator, then the result will show that all of the global markets are efficient. Nevertheless, the negative of the mean-reversion (MR) RSI strategy return is approximately equal to the return for the momentum (MM) RSI strategy.

When: (MR-RSI Return) - (Buy and Hold Return) = (MR-Excessive Return),

given that: (MM-RSI Return) ≈ - (MR-RSI Return) ,

it follows: (MM-Excessive Return) = - (MR-Excessive Return)
- 2(Buy and Hold Return).

This explains why the excessive return for Indonesia is extremely negative; as it implies the high excessive return for the momentum RSI strategy. All in all, the low t-stat for Indonesia, Malaysia, Singapore, Switzerland, and Thailand can be translated into high t-stat under the momentum RSI strategy, indicating that markets are inefficient. When none of the mean reversion RSI excessive returns is positive, one may infer that

momentum anomaly dominates the mean reversion anomaly. However, further proof is required.

6 DISCUSSION AND CONCLUSION

This paper investigates the global weak-form market efficiency through selections of technical analysis including the static, semi-dynamic, and dynamic momentum strategies, oscillation strategy, and the relative strength index strategy. As long as one of the tests shows that the market is inefficient, then the market is inefficient because it is possible to extract excessive profit based on technical analysis. Of the 24 country indexes and 1 world index, only 10 are proven to be efficient as there are inadequate evidences to prove the existence of excessive profits beyond the buy and hold strategy. These 10 countries are Australia, Belgium, Denmark, France, Germany, Japan, Netherlands, Switzerland, United Kingdom, and United States. In the most extreme, none of the technical strategies employed in this paper produces positive excessive profits in United States and Germany. All of these countries are fully developed, and so are their financial sectors. The technical traders in these countries would have already swept the momentum and the mean-reversion anomaly, leaving no room for excessive profit under the strategies in the paper. On the other hand, the most significant inefficient markets proven in this paper are Indonesia, Korea, Malaysia, and Thailand. These countries are predominantly categorized as the "emerging markets"; inefficiency in their financial market is understandable. Through out the paper, Canada is actually considered inefficient as significant excessive profits can be extracted in 3 of

the 7 technical strategies. The physical distance of Canada and United States is very close, but the market efficiency is widely apart.

This paper also discovered several properties of the trading strategies:

(1) First of all, trends are not discovered in the static momentum strategy as the number of observation days increase. The market characteristic in each country disturbs the trend in the global basis.

(2) The sell signals are as important as the buy signals. To illustrate, all the market returns increases significantly from the semi-dynamic strategy to the fully dynamic strategy, with the only exception of Taiwan.

(3) A more customization of the strategies results in better return. For example, dynamic strategy is better than the semi-dynamic one, which is also better than the pure static momentum strategies.

(4) Schwager's statement regarding oscillation does not coincide with the evidence in this paper. He mentions that "[o]scillators perform well when a market is in a trading range - that is, a sideways trend. They work poorly, however, when a market is in a strong uptrend or downtrend. (Schwager 1996, p.556)" Indonesia, Malaysia, and Thailand, are markets in very strong uptrend or downtrend. However, their oscillation returns are the highest among all.

(5) However, another statement from Schwager found in this context regarding the relative strength index strategy: "Traders should not automatically sell markets that are over bought or buy markets that are oversold. Although

such a strategy may work well in a trading-range market, it will be disastrous in a trending market. (Schwager 1996, p.524)" The mean-reversion RSI strategy employed in this paper is based on the belief that an over-sold market would revert as a winner and that an over-bought market would revert as a loser. Indeed the returns in Indonesia, Malaysia, and Thailand are drastically low. In strong trendy markets like them, over-bought should be treated as buy signals and *vice versa*. The RSI strategy should be best exploited as a momentum strategy.

The result also demonstrates that the technical trading strategies work the best during the periods of negative market return and the periods of moderate growth. The possibility to filter losses during the negative market return period makes the strategies attractive for the fund managers trying to hedge their funds and minimizing downside risks. It signifies that it is possible to filter the losses during a year. In addition, as this paper demonstrates the significance excessive profits, fund managers are encouraged to diversify their investments country-wisely and maximize the portfolio value in the inefficiency markets.

APPENDIX - RESULT TABLES

Table 1 The Performance of the 3 Static Momentum Strategies for the Whole Sample 15 Years.

Index	Strategy			
	Buy and Hold	3 days Static Momentum	6 days Static Momentum	12 days Static Momentum
WORLD	4.75%	5.62%	1.86%	3.80%
AUSTRALIA	4.67%	3.18%	0.43%	3.66%
AUSTRIA	7.06%	12.76%	12.77%	7.77%
BELGIUM	5.33%	6.31%	2.31%	0.50%
CANADA	6.38%	10.85%	8.03%	5.40%
DENMARK	9.07%	5.89%	3.64%	4.07%
FRANCE	7.23%	1.70%	0.93%	1.96%
GERMANY	6.04%	5.11%	0.25%	2.63%
HONG KONG	7.75%	8.71%	5.35%	3.47%
INDONESIA	-3.51%	26.86%	15.17%	14.44%
ITALY	3.92%	5.96%	1.94%	1.35%
JAPAN	-4.13%	-3.59%	-4.25%	-2.79%
KOREA	-0.88%	6.86%	9.82%	4.47%
MALAYSIA	3.25%	16.63%	10.21%	4.60%
NETHERLANDS	7.19%	1.06%	-1.82%	2.52%
NORWAY	6.27%	7.67%	8.22%	3.58%
SINGAPORE	4.71%	11.21%	7.64%	4.14%
SOUTH AFRICA	5.73%	10.50%	7.75%	4.44%
SPAIN	6.07%	2.39%	-0.50%	6.07%
SWEDEN	9.20%	4.90%	2.83%	3.61%
SWITZERLAND	10.23%	10.10%	4.38%	5.60%
TAIWAN	-0.40%	10.15%	0.22%	4.96%
THAILAND	0.18%	20.42%	13.31%	14.78%
UK	5.87%	1.74%	0.74%	0.02%
US	8.93%	0.31%	0.80%	2.34%

Table 2 **The Performance of the Semi-Dynamic, Dynamic, Oscillation, and Relative Strength Index Strategies for the Whole Sample 15 Years.**

Index	Strategy				
	Buy and Hold	Semi-Dynamic	Dynamic	Oscillation	Relative Strength Index
WORLD	4.75%	12.26%	17.85%	4.60%	2.00%
AUSTRALIA	4.67%	4.42%	8.58%	3.69%	0.81%
AUSTRIA	7.06%	13.65%	18.22%	9.11%	-0.63%
BELGIUM	5.33%	8.07%	11.46%	3.87%	2.85%
CANADA	6.38%	11.09%	13.25%	5.72%	-0.29%
DENMARK	9.07%	8.57%	12.74%	2.17%	3.48%
FRANCE	7.23%	4.97%	11.55%	0.84%	2.73%
GERMANY	6.04%	3.95%	6.22%	4.59%	1.13%
HONG KONG	7.75%	17.42%	20.00%	8.48%	0.25%
INDONESIA	-3.51%	30.06%	40.44%	24.36%	-26.04%
ITALY	3.92%	11.51%	13.35%	1.92%	1.22%
JAPAN	-4.13%	-5.60%	2.00%	-4.76%	-4.78%
KOREA	-0.88%	7.00%	13.90%	7.15%	-5.83%
MALAYSIA	3.25%	21.87%	29.92%	16.47%	-8.00%
NETHERLANDS	7.19%	2.55%	8.83%	-0.39%	3.25%
NORWAY	6.27%	13.54%	18.40%	8.32%	-2.71%
SINGAPORE	4.71%	12.99%	20.04%	8.20%	-5.60%
SOUTH AFRICA	5.73%	13.76%	22.96%	11.81%	-1.46%
SPAIN	6.07%	9.66%	16.16%	5.11%	4.61%
SWEDEN	9.20%	9.83%	20.53%	7.56%	-1.46%
SWITZERLAND	10.23%	7.25%	11.13%	5.01%	2.69%
TAIWAN	-0.40%	10.45%	7.34%	5.70%	-9.09%
THAILAND	0.18%	26.78%	36.48%	17.40%	-12.95%
UK	5.87%	4.77%	7.78%	-2.47%	1.60%
US	8.93%	6.22%	8.50%	1.66%	4.64%

Table 3 Return of All the Strategies Listed Yearly

Year	Buy and Hold	3-Day Static	6-Day Static	12-Day Static	Semi-Dynamic	Dynamic	Oscillation	RSI
1989	24.64%	22.99%	17.35%	11.48%	25.03%	21.86%	21.98%	7.15%
1990	-16.18%	-0.32%	-0.58%	2.22%	5.53%	19.12%	2.13%	-12.16%
1991	7.04%	6.49%	11.48%	6.02%	8.85%	18.78%	10.08%	3.41%
1992	-8.33%	-3.30%	-0.93%	-0.32%	-0.21%	5.97%	-0.49%	-4.04%
1993	37.05%	25.96%	17.31%	14.27%	24.98%	29.38%	25.73%	10.97%
1994	-7.94%	-0.44%	-3.87%	-2.73%	4.60%	10.16%	-1.18%	0.41%
1995	16.79%	12.31%	9.17%	4.50%	12.83%	13.61%	9.82%	3.59%
1996	6.53%	3.82%	2.98%	2.55%	10.09%	10.70%	3.56%	2.02%
1997	-14.12%	0.78%	-6.27%	4.01%	10.72%	17.12%	-4.80%	-15.52%
1998	6.84%	13.24%	-0.05%	6.49%	16.20%	22.23%	3.36%	-16.28%
1999	21.91%	22.30%	14.23%	7.65%	16.93%	20.59%	17.24%	8.14%
2000	-14.04%	-5.88%	-6.70%	-5.38%	-2.58%	5.09%	-4.24%	-6.14%
2001	-22.00%	-9.49%	-7.22%	-2.18%	-11.23%	-0.75%	-6.49%	-16.50%
2002	-13.28%	-6.93%	-8.98%	-6.73%	1.08%	9.36%	-9.10%	-10.89%
2003	40.33%	30.94%	18.69%	17.35%	26.98%	23.62%	22.14%	5.56%

Table 4 Test Result for 3-Day Static Momentum Strategy.

	Excessive Return	Standard Error	t-Stat	Significance
WORLD	0.8126%	2.5383%	0.3201	-
AUSTRALIA	-0.8091%	2.4824%	-0.3259	-
AUSTRIA	5.1907%	4.1313%	1.2564	-
BELGIUM	1.4928%	3.3376%	0.4473	-
CANADA	5.0218%	2.6645%	1.8847	5%
DENMARK	-3.2826%	2.1877%	-1.5004	-
FRANCE	-5.3789%	2.8170%	-1.9094	-
GERMANY	-1.3751%	3.1796%	-0.4325	-
HONG KONG	0.3492%	4.5629%	0.0765	-
INDONESIA	30.1692%	10.3151%	2.9248	1%
ITALY	2.0943%	3.6556%	0.5729	-
JAPAN	1.4782%	3.7966%	0.3894	-
KOREA	7.7429%	4.9332%	1.5695	10%
MALAYSIA	12.3835%	7.7377%	1.6004	10%
NETHERLANDS	-6.0285%	2.1187%	-2.8453	-
NORWAY	2.5552%	3.1494%	0.8113	-
SINGAPORE	7.6328%	4.5480%	1.6783	10%
SOUTH AFRICA	4.2908%	3.6171%	1.1863	-
SPAIN	-3.0374%	2.3172%	-1.3108	-
SWEDEN	-3.7093%	5.2252%	-0.7099	-
SWITZERLAND	-0.1152%	3.2140%	-0.0358	-
TAIWAN	11.8981%	7.3896%	1.6101	10%
THAILAND	21.9709%	8.0521%	2.7286	1%
UK	-3.6488%	2.5797%	-1.4144	-
US	-9.0814%	2.2606%	-4.0173	-

Table 5 Test Result for 6-Day Static Momentum Strategy.

	Excessive Return	Standard Error	t-Stat	Significance
WORLD	-3.1400%	3.2299%	-0.9722	-
AUSTRALIA	-4.1754%	3.0529%	-1.3677	-
AUSTRIA	5.0302%	4.3881%	1.1463	-
BELGIUM	-2.7209%	3.0251%	-0.8994	-
CANADA	1.7918%	2.9707%	0.6032	-
DENMARK	-5.2540%	3.4649%	-1.5163	-
FRANCE	-6.3818%	3.6752%	-1.7365	-
GERMANY	-7.0128%	4.3799%	-1.6011	-
HONG KONG	-3.5765%	5.1790%	-0.6906	-
INDONESIA	17.4178%	8.0781%	2.1562	5%
ITALY	-2.2708%	4.2995%	-0.5282	-
JAPAN	0.1026%	5.7287%	0.0179	-
KOREA	10.7614%	6.8758%	1.5651	10%
MALAYSIA	6.4572%	7.2887%	0.8859	-
NETHERLANDS	-9.7022%	3.2270%	-3.0066	-
NORWAY	3.5524%	4.0712%	0.8726	-
SINGAPORE	2.3294%	6.1370%	0.3796	-
SOUTH AFRICA	2.9309%	5.7774%	0.5073	-
SPAIN	-7.2615%	4.0117%	-1.8101	-
SWEDEN	-5.2671%	5.8576%	-0.8992	-
SWITZERLAND	-6.6203%	3.0336%	-2.1823	-
TAIWAN	1.0761%	8.9703%	0.1200	-
THAILAND	10.6886%	7.1465%	1.4956	10%
UK	-5.4327%	2.7213%	-1.9964	-
US	-8.2636%	2.6085%	-3.1679	-

Table 6 Test Result for 12-Day Static Momentum Strategy

	Excessive Return	Standard Error	t-Stat	Significance
WORLD	-0.9440%	3.3492%	-0.2819	-
AUSTRALIA	-0.4327%	3.6419%	-0.1188	-
AUSTRIA	0.9558%	5.1473%	0.1857	-
BELGIUM	-5.1318%	3.2718%	-1.5685	-
CANADA	-0.6245%	4.3376%	-0.1440	-
DENMARK	-4.4064%	4.2178%	-1.0447	-
FRANCE	-5.2273%	4.8053%	-1.0878	-
GERMANY	-4.5536%	4.7009%	-0.9687	-
HONG KONG	-5.3319%	7.1229%	-0.7486	-
INDONESIA	17.5135%	14.7563%	1.1868	-
ITALY	-2.5053%	3.7254%	-0.6725	-
JAPAN	1.3491%	5.8629%	0.2301	-
KOREA	4.8210%	5.7669%	0.8360	-
MALAYSIA	1.4996%	9.5683%	0.1567	-
NETHERLANDS	-4.7598%	3.3466%	-1.4223	-
NORWAY	-1.6003%	4.5332%	-0.3530	-
SINGAPORE	-0.7152%	6.2058%	-0.1153	-
SOUTH AFRICA	-0.9461%	7.8022%	-0.1213	-
SPAIN	0.2066%	4.0454%	0.0511	-
SWEDEN	-4.9466%	5.6354%	-0.8778	-
SWITZERLAND	-5.2479%	3.3975%	-1.5446	-
TAIWAN	6.9632%	10.5960%	0.6572	-
THAILAND	15.3915%	11.6229%	1.3242	-
UK	-5.5603%	2.6624%	-2.0885	-
US	-6.8714%	3.6529%	-1.8811	-

Table 7 Test Result for Semi-Dynamic Momentum Strategy

	Excessive Return	Standard Error	t-Stat	Significance
WORLD	7.0899%	3.3401%	2.1227	5%
AUSTRALIA	0.5413%	2.1435%	0.2525	-
AUSTRIA	7.2863%	4.1104%	1.7727	5%
BELGIUM	2.4915%	3.5208%	0.7076	-
CANADA	5.6041%	3.0534%	1.8354	5%
DENMARK	-0.8467%	3.1428%	-0.2694	-
FRANCE	-2.1937%	2.4277%	-0.9036	-
GERMANY	-3.3188%	3.4507%	-0.9618	-
HONG KONG	10.8416%	5.9451%	1.8236	5%
INDONESIA	30.2900%	10.1668%	2.9793	1%
ITALY	8.3597%	3.7357%	2.2378	5%
JAPAN	-2.1646%	4.6655%	-0.4640	-
KOREA	7.1799%	5.9470%	1.2073	-
MALAYSIA	17.7046%	10.4320%	1.6971	10%
NETHERLANDS	-6.1032%	3.0049%	-2.0311	-
NORWAY	8.7512%	4.0539%	2.1587	5%
SINGAPORE	7.7674%	5.8015%	1.3389	-
SOUTH AFRICA	8.1843%	5.1531%	1.5882	10%
SPAIN	2.6276%	3.6894%	0.7122	-
SWEDEN	1.1959%	4.3968%	0.2720	-
SWITZERLAND	-3.1787%	2.1246%	-1.4961	-
TAIWAN	11.8586%	7.6185%	1.5565	10%
THAILAND	24.6146%	9.7998%	2.5117	1%
UK	-0.7857%	2.8911%	-0.2718	-
US	-2.8132%	2.7610%	-1.0189	-

Table 8 Test Result for Dynamic Momentum Strategy

	Excessive Return	Standard Error	t-Stat	Significance
WORLD	13.2832%	4.3658%	3.0426	1%
AUSTRALIA	3.5549%	3.2266%	1.1017	-
AUSTRIA	11.3330%	5.8442%	1.9392	5%
BELGIUM	5.7372%	4.5071%	1.2729	-
CANADA	7.0227%	3.4096%	2.0597	5%
DENMARK	3.6461%	4.5112%	0.8082	-
FRANCE	4.2759%	3.6576%	1.1691	-
GERMANY	-0.5607%	5.4518%	-0.1029	-
HONG KONG	11.3558%	5.5562%	2.0438	5%
INDONESIA	40.5820%	15.2863%	2.6548	1%
ITALY	9.8038%	4.8261%	2.0314	5%
JAPAN	5.6063%	5.9197%	0.9471	-
KOREA	14.0053%	6.4861%	2.1593	5%
MALAYSIA	26.8795%	10.8307%	2.4818	5%
NETHERLANDS	0.7873%	4.7601%	0.1654	-
NORWAY	13.0277%	5.4335%	2.3977	5%
SINGAPORE	14.6762%	5.7987%	2.5310	5%
SOUTH AFRICA	17.3890%	8.0168%	2.1691	5%
SPAIN	9.7942%	5.2482%	1.8662	5%
SWEDEN	12.8824%	6.8940%	1.8686	5%
SWITZERLAND	0.5454%	3.3660%	0.1620	-
TAIWAN	7.6788%	9.4418%	0.8133	-
THAILAND	35.4565%	11.8102%	3.0022	1%
UK	1.6201%	2.8216%	0.5742	-
US	-0.2946%	3.0022%	-0.0981	-

Table 9 Test Result for Oscillation (Dual Exponential Moving Average) Strategy

	Excessive Return	Standard Error	t-Stat	Significance
WORLD	-0.1287%	2.2508%	-0.0572	-
AUSTRALIA	-0.0870%	2.3422%	-0.0371	-
AUSTRIA	2.5835%	3.4243%	0.7545	-
BELGIUM	-1.3663%	3.2252%	-0.4236	-
CANADA	0.2563%	3.5178%	0.0729	-
DENMARK	-6.4339%	2.6631%	-2.4160	-
FRANCE	-6.0416%	2.7752%	-2.1770	-
GERMANY	-1.8019%	3.9294%	-0.4586	-
HONG KONG	0.4231%	5.2600%	0.0804	-
INDONESIA	26.3048%	10.0860%	2.6080	1%
ITALY	-1.7219%	3.2266%	-0.5336	-
JAPAN	-0.8395%	5.4419%	-0.1543	-
KOREA	8.5454%	5.6727%	1.5064	10%
MALAYSIA	13.8978%	7.1164%	1.9529	5%
NETHERLANDS	-8.0157%	2.8543%	-2.8083	-
NORWAY	3.9346%	4.2478%	0.9263	-
SINGAPORE	3.9001%	5.1721%	0.7541	-
SOUTH AFRICA	6.1064%	6.3458%	0.9623	-
SPAIN	-0.8429%	3.2650%	-0.2582	-
SWEDEN	-0.9767%	4.9867%	-0.1959	-
SWITZERLAND	-5.1805%	2.6623%	-1.9459	-
TAIWAN	7.5153%	5.6370%	1.3332	-
THAILAND	16.1513%	7.2995%	2.2127	5%
UK	-7.6809%	3.1744%	-2.4196	-
US	-7.7424%	2.2754%	-3.4026	-

Table 10 Test Result for Relative Strength Index Strategy

	Excessive Return	Standard Error	t-Stat	Significance
WORLD	-3.4033%	3.4208%	-0.9949	-
AUSTRALIA	-3.6702%	3.8302%	-0.9582	-
AUSTRIA	-7.5437%	6.6942%	-1.1269	-
BELGIUM	-2.5393%	4.3489%	-0.5839	-
CANADA	-5.9483%	4.0045%	-1.4854	-
DENMARK	-4.8851%	4.7828%	-1.0214	-
FRANCE	-4.7990%	3.8065%	-1.2607	-
GERMANY	-4.6979%	5.5053%	-0.8533	-
HONG KONG	-8.5239%	6.3300%	-1.3466	-
INDONESIA	-27.2244%	9.2899%	-2.9305	§
ITALY	-3.4471%	4.5187%	-0.7628	-
JAPAN	-0.3623%	4.0922%	-0.0885	-
KOREA	-6.1371%	6.3750%	-0.9627	-
MALAYSIA	-11.6185%	5.2333%	-2.2201	§
NETHERLANDS	-4.9445%	3.4574%	-1.4301	-
NORWAY	-7.4611%	5.4394%	-1.3717	-
SINGAPORE	-11.1409%	5.5913%	-1.9926	§
SOUTH AFRICA	-7.4838%	4.6035%	-1.6257	-
SPAIN	-2.6167%	4.7245%	-0.5539	-
SWEDEN	-8.8046%	6.1544%	-1.4306	-
SWITZERLAND	-8.5916%	4.6644%	-1.8420	§
TAIWAN	-8.0459%	6.4680%	-1.2440	-
THAILAND	-14.8416%	5.3617%	-2.7681	§
UK	-3.8147%	3.0065%	-1.2688	-
US	-4.4385%	3.4230%	-1.2967	-

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