Tests of Technical Trading Strategies in the Emerging Equity Markets of Latin America and Asia

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May 1998

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ABSTRACT

This study examines the potential profit of technical trading strategies among 10 emerging equity markets of Latin American and Asia: Argentina, Brazil, Chile, Mexico, India, Korea, Malaysia, Philippines, Taiwan, and Thailand. We use daily inflation adjusted returns for the January 1982 to April 1995 period. Ten different variable moving average trading models are assessed through a bootstrapping simulation. The average buy-sell returns difference after trading costs for each strategy and country are compared to a buy and hold strategy. Taiwan, Mexico and Thailand emerge as markets where technical trading strategies may be profitable. We found no strong evidence of profitability for the other markets.

I. INTRODUCTION

Technical analysts have long relied on the premise of predicting market returns through identifying patterns in past stock market prices. Belief in past price patterns in security movements violates the random walk hypothesis -- the weak form of stock market efficiency. Little is known, however, regarding the efficiency of the emerging stock markets as compared to the developed markets of the highly industrialized countries.

The purpose of this study is to examine the efficacy of using technical trading strategies in the emerging markets of Latin America and Asia to earn profits in excess of a simple buy & hold philosophy. The results demonstrate that, after trading costs are factored in, clearly superior profits cannot be achieved by technical trading over a simple buy & hold strategy in most cases. The findings contribute to a more comprehensive understanding of the nature of the return generating process among some of the world's largest emerging equity markets.

II. PREVIOUS RESEARCH

Early empirical research by Roberts (1959) and Brealey (1969) has presented evidence supporting the weak form of market efficiency. These studies typically focus on the inability of investment trading strategies to generate significant economic returns. If markets follow a random walk, then technical trading strategies would have no merit. Fama and Blume (1966) and Jensen and Benington (1970) find that technical trading rules cannot be successfully used in the U.S. equity markets. Yet, evidence of seasonalities in the US stock market is plentiful. Cadsby and Ratner (1992) find support for seasonal effects in international equity markets while Agrawal and Tandon (1994) and Aggarwal and Rivoli (1989) identify seasonalities in emerging markets. Urrutia (1995) rejects the random-walk hypothesis for Latin American emerging markets.

Recent evidence, however, by Brock, Lakonishok, and Le Baron (1992) and Sweeney (1986) indicates that some technical trading rules do have the ability to forecast price changes in the US equity market and in the currency market. In contrast, Hudson et al. (1996) find that the Brock et al. (1992) trading rules have some ability to predict the FT30 series of returns but that no significant gains are found after factoring trading costs in. Ready (1997), using intraday data for the US, find that the Brock et al. trading rules do not beat a buy and hold strategy due to trading costs and the time that actual trades resulting from the strategy signals can be placed. For some Asian countries and for an earlier period than our period of study, Bessembinder and Chan (1995) find that the Brock et al. trading rules can be profitable. Thus, the controversy is still open.

The profitability of technical trading rules in emerging markets may be associated with the persistence of returns, or autocorrelation, in these markets. Harvey (1995a) finds that the autocorrelation in emerging markets is much higher than in developed markets. He also suggests that the level of autocorrelation is directly associated with the size and the degree of concentration of the market. Predictability has also been addressed by Harvey (1995b) who utilizes a pricing model. Harvey contends that emerging market returns seem to be predictable when using international and local risk factors. Harvey used, among other data, the Morgan Stanley Capital International World Index and a foreign exchange index as international proxies. Erb, Harvey, and Viskanta (1996) find that equity returns and volatility are predictable for a group of 48 countries by using credit risks obtained from *Institutional Investor* as the sole explanatory variable. Diamonte, Liew, and Stevens (1996) indicate that political risk measures are capable of predicting the returns in emerging markets better than in developed markets. However, predictability does not necessarily imply inefficiency if the application of a known trading strategy does not generate systematic economic gains to its users. We will test if market participants can exploit this predictability of emerging market returns with significant economic gains by market participants that utilize the technical trading strategies we study.

III. THE DATA

The sample consists of ten large emerging markets. Daily local index closing levels are obtained for Argentina (Bolsa Indice General), Brazil (Indice BOVESPA), Chile (Indice General de Precios), India (Bombay Sensitive), Korea (Seoul Composite Index), Malaysia (Kuala Lumpur Composite Index), Mexico (Indice de Precios

y Cotaciones), Philippines (Manila Composite Index), Taiwan (Taipei Weighted Price Index), and Thailand (Bangkok S.E.T.). The sources of the indexes were each country's stock exchanges for earlier periods and The Financial Times database for later periods. The daily index levels are collected beginning in January 1982 through April 1995. The beginning period of January 1982 is selected arbitrarily.[1] The indices for the United States (S&P 500) and Japan (Nikkei 225) are also included in the sample for comparison purposes.

We use daily inflation adjusted returns. Many of these economies have been closed to foreign investors until quite recently. Real returns may be more relevant than dollar returns. Annualized monthly inflation rates for each country were obtained from the *International Financial Statistics* database. Each monthly inflation rate was divided by 240 to estimate for the daily weekday inflation[2]. The daily returns are computed as the difference between day *t* nominal return and the inflation rate computed for that day as in equation 1:

$$IAR_{i,t} = \left(\frac{I_{i,t} - I_{t-1}}{I_{t-1}} \right) - \left(\frac{INF_{i,m}}{240} \right) \quad (1)$$

where $IAR_{i,t}$ is the inflation adjusted return for country *i* on day *t*, $I_{i,t}$ is the closing stock market index for country *i* on day *t*, and $INF_{i,m}$ is the annualized monthly inflation for country *i* in month *m* when day *t* occurred. When the closing level of a national market index was missing due to a local closure or holiday, we repeated the previous day closing value. We tested, but do not report here, for the stationarity of each series using the Dickey-Fuller procedure. All series of inflation adjusted returns are stationary.

Table 1 reports daily means and standard deviations in annualized percentage form for the inflation adjusted returns. Stocks in Argentina and Brazil have underperformed inflation, particularly in the years of hyper inflationary processes in the late 80's and early 90's. These countries obviously present the largest volatility[3]. The first autocorrelation

[1] Three large emerging markets, South Africa, Indonesia, and China, are omitted from this study. When the data was initially collected in 1992, South Africa was not listed by the IFC as "emerging," and China and Indonesia were smaller markets with limited data available. According to the IFC (1995), the sample used in this study represents 71.4% of the emerging market capitalization.

[2] This assumes 12 months with 20 trading days in each month as an approximation. We realize some of the markets opened on Saturdays, particularly in the earlier years of the sample. However, we decided to keep this as an approximation for the number of trading days since there are also a number holidays and closures in these markets and the actual number of trading days hovers around 240 per year.

[3] It is obvious that no nominal returns can be less than -100%. However, real returns may. If inflation was 200% and the market was up only 80% in one year, our inflation-adjusted return would be -120% for that year. The bad

is presented for each market. Significant autocorrelation suggests potential patterns in the data. The larger the magnitude of the autocorrelation, the greater the potential weak form market inefficiency. There is a significant first-order autocorrelation for all Latin markets plus India, Malaysia, Taiwan, Thailand, and the US. After we present our trading strategies results we can see if profitability seems to be influenced by the presence of autocorrelation. Finally, none of the series seems to be normal. All the kurtosis coefficients and most of the skewness coefficients are significant. A Kolmogorov-Smirnov test, not reported here, also indicated that the series are not normal.

IV. TRADING STRATEGY METHODOLOGY & RESULTS

To avoid "data mining," this study does not search for patterns in the data on an *ex post* basis. Instead, the technical trading rules used by Brock, Lakonishok, and LeBaron (1992) are applied with a bootstrapping technique. Specifically, 10 Variable Length Moving Average (VMA) models are analyzed which have been widely known to technical analysts. Moving average trading models take advantage of positive serial correlation in equity returns. A trading signal usually follows a large movement in stock price under the assumption that the autocorrelation bias in the time series trend will continue in the same direction.

The VMA rules analyzed are as follows: 1-50, 1-150, 5-150, 1-200, 2-200, where the 1, 2, and 5 represent the number of days in the short moving average, and the 50, 150, and 200 represent the number of days in the long moving average. A buy signal is indicated when the short moving average exceeds the long moving average:

$$\frac{\sum_{s=1}^{S} R_{i,t}}{S} > \frac{\sum_{l=1}^{L} R_{i,t-l}}{L} = Buy \qquad (2)$$

where $R_{i,t}$ is the daily return in period S (1, 2, or 5 days), and $R_{i,t-1}$ is the return used to compute the long average over a period of L days (50, 150 or 200 days). This test is repeated daily with the changing moving averages throughout the sample. The buy position is a long position in the index and is maintained until a sell signal is indicated as per equation 3. With the sell sign, the investor is out of the market, not short. Since we already use inflation-adjusted returns, no interest is earned during the "sell" days. After Brock et al. (1992), the strategies are

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performance of the Argentinean and Brazilian markets combined with extreme volatility during the 80's has been documented by Barry and Rodriguez (1998), among others.

effective if the average buy minus sell (buy-sell) signal is positive and significant and greater than a buy and hold alternative after trading costs.

$$\frac{\sum_{s=1}^{S} R_{i,t}}{S} < \frac{\sum_{l=1}^{L} R_{i,t-l}}{L} = Sell \qquad (3)$$

The bootstrapping procedure was performed by scrambling the actual inflation adjusted return data by withdrawing with replacement from the original series to form a simulated series. The trading strategies are then applied to the simulated series and the mean buy and sell returns are computed for each iteration. This process is repeated 500 times. From the distribution of mean returns built from the simulated series we calculate the proportion that shows a return that is greater than that computed with the actual series. After Brock et al., we use this statistics as a simulated *p-value*. The less the *p-value* the more significant and less due to chance are the results of the strategies on the actual series. In our tables we only report the *p-values* for the buy-sell difference. Significant (less than .05 *p-value*) difference in buy-sell day equity returns demonstrates the effectiveness of the VMA rules to forecast equity returns. This is the same procedure used by Bessembinder and Chan (1995) for nominal Asian returns from an earlier period. To minimize measurement error due to nonsynchronous trading noted by Scholes and Williams (1977), the buy-sell signal is followed by a one-day lag before the trade takes place.

This study differs from Brock, Lakonishok, and LeBaron (1992) in one important way. Brock et al evaluate each rule with a trading band of 0 and 1% of returns. Given the large difference in volatility across both time and markets, this study employs a trading band of 0 and 1 standard deviations of the actual inflation adjusted return series[4]. A zero band classifies each return as either a buy or sell. While a band of 1 standard deviation would emit a buy or sell signal only when the short moving average crosses the trading band. The current position is maintained until the short average crosses the long average band once again from the opposite direction, minimizing the number of trades. For example, model (1) is modified as follows:

[4] A 1% return change trading band is equivalent to a 15.5% annualized standard deviation according to our annualization method used for table 1. This was the band used by Bessembinder and Chan (1995). From table 1 we can see that only the US, Malaysia, and Chile show this kind of volatility. All other countries have a much higher volatility. Therefore, our 1 standard deviation trading band would generate less trades than the 1% return change band, would be more cost effective, and would account for the differences in country volatilities.

$$\frac{\sum_{s=1}^{S} R_{i,t}}{S} > \frac{\sum_{l=1}^{L} R_{i,t-l} + \sqrt{\frac{n\sum_{n=1}^{n} R_{i,t}^2 - (\sum_{n=1}^{n} R_{i,t})^2}{n(n-1)}}}{L} = Buy \qquad (4)$$

where *n* is the number of daily returns in each series.

Table 2 reports the mean daily returns (%) of the buy and sell signals generated by the 10 VMA trading models without a trading band. The buy-sell returns are individually averaged for each trading model and country over time. The buy-sell returns are then averaged across all VMA models within each country for the 500 iterations on the simulated data. Under the model with 0 standard deviations, the buy signal returns are greater than the sell signal returns across all models and countries except for the USA for all VMA versions[5], Japan and Brazil for one version of the VMA, and India for three versions of the VMA out of five used. Fifty out of sixty VMA versions (12 countries with 5 versions each) have buy signals greater than the sell signals. The Latin American markets appear to have the widest disparity of buy-sell returns. However, only in Mexico the strategies seem to be significant in that region. In Asia, all countries, except India, present strategies with potentially significant results, with four out five versions of the VMA strategies being significant in Taiwan and Thailand.

Our results are consistent with those of Bessembinder and Chan (1995) for Taiwan and Thailand. They used nominal returns for the January 1975 to December 1989 period. At the 5% significance level for the p-value, they find that 2 versions of the VMA strategy are significant for Japan, 1 for Korea, 5 for Malaysia, 3 for Taiwan, and 5 for Thailand. We find these numbers to be 1, 1, 1, 3, and 4, respectively. The use of inflation adjusted returns over a more recent period reduces the significance of the VMA strategies. Besides, for countries not tested by Bessembinder and Chan (1995) we find significance only for one version of the strategy in the Philippines and for four versions in Mexico. Mexico, Taiwan and Thailand seem to be the markets with more potential for profitability of technical trading strategies.

Table 3 presents the results for the 1 standard deviation trading band. The number of buy signals which are greater than the sell signals goes down to 37 from 50 in table 2. The number of significant p-values is greatly

[5]This is consistent with Ready (1997) for the eighties and nineties sub periods with NYSE stocks. Brock et al. (1992) examine the Dow from 1897 up to 1986. Ready also finds significance in the VMA strategies for earlier periods but not for the last 15 or so years.

reduced as well. While there were 15 versions of the VMA strategy with significant buy-sell signals with no trading band, there are only 8 significant versions of the strategies now. Thailand no longer presents any significant version of the VMA strategy while other countries either present the same number of significant strategies or less. Brazil is the exception, presenting one significant strategy with the trading band while it had none without the trading band. Here our results diverge from those of Bessembinder and Chan (1995). The reason is that we use a wider trading band for most countries. While their band was a 1% return change fixed across countries with disparate volatilities, ours is 1 standard deviation. Therefore, our trading band should lead to more conservative results, and such was the case. While they find 16 significant strategies without a trading band and we find 15, they still find 15 significant strategies with their narrower trading band while we find only 8 for the countries common to both studies.

Tables 4 and 5 provide summary information of the 10 VMA trading models for the 0 and 1 standard deviation trading bands, respectively. These tables compare potential returns of the VMA trading rules with a simple buy & hold strategy considering trading costs. The trading costs are estimates[6] and are assumed constant throughout the sample period. Under the 0 standard deviation model, an enormous number of trades would have to occur and the trading costs are quite demanding on the strategies.

Considering the last two rows in table 4 for the average of the returns for all VMA strategies for a country, only Taiwan and Thailand present clearly superior returns for the VMA strategies. The superiority for the strategies in Korea and Mexico is marginal. The results in table 5 are similar, with Taiwan and the Philippines with clearly superior returns for the VMA strategies and Korea and Mexico with marginal superiority. For most countries there is no evidence that these strategies could generate superior returns compared to a buy & hold strategy.

Considering only the significant strategies for each country from tables 2 and 3, Taiwan, Mexico and Thailand emerge from tables 4 and 5 as the countries with the largest number of significant and profitable trading strategies after trading costs and relative to the buy & hold alternative.

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[6] Trading costs for Japan, Korea, Malaysia, Thailand, and Taiwan are provided by Rhee, Chang, and Ageloff (1990), including brokers fee and taxes. Price (1994) provides the costs in Argentina (excludes fees and taxes). Costs for India and the Philippines are provided by *Birinyi Associates*. Costs for Brazil (excludes fees and taxes),

V. CONCLUSIONS

This study applies 10 Variable Length Moving Average (VMA) models to test the effectiveness of technical trading in 10 large emerging equity markets in Asia and Latin America, and the U.S. and Japan from 1982 through April 1995. Daily inflation adjusted returns are utilized. The significance of the buy-sell signals are assessed through a bootstrapping simulation

The findings indicate that VMA trading models do not possess widespread ability to profitably forecast future stock price movements in most of the emerging markets of this study. For those strategies that showed significance from the bootstrapping simulation, after considering trading costs and a buy & hold strategy, we found five profitable strategies for Mexico and Taiwan, three for Thailand, two for the Philippines, one for Brazil, Japan, Korea and Malaysia and none for Argentina, Chile, India, and the US. Mexico and Taiwan, and possibly Thailand, emerge as markets where technical trading strategies may have potential.

Taiwan has the lowest trading costs and the highest turn over of all markets with a significant first order autocorrelation. This is a microstructure environment that is friendly to trading strategies such as those examined in this paper. Thailand also has relatively low trading costs and also shows a significant first order autocorrelation. However, the case of Mexico is more puzzling. Its trading costs are not low and therefore the turnover is not particularly large. Its first order autocorrelation is significant but so are those of countries where the trading strategies do not work. The question of what could explain why Mexico, Taiwan, and Thailand would be more prone to yield profits from technical strategies with such an apparently different microstructure is left for future research.

Chile, and Mexico are provided by the individual local exchanges. The costs for trading in the U.S. are the 1996 costs of trading with discount broker Charles Schwab.

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TABLE 1

Descriptive Statistics For the Annualized Daily Inflation Adjusted Returns (IAR) in the January 1982 to April 1995 Period and Market Information[1,2]

Country	Table Identifiers	Annualized IAR Mean[3] (%)	Annualized IAR Standard Deviation[4] (%)	1-day Autocorr.	Skewness	Kurtosis	(US bil.) Market Cap.	Number of Listed Firms	IFC Index Concen-tration	Market Turn Over	Trading Cost per Trade[5]
Developed Markets:											
Japan	JAP	4.08	18.14	0.10	-.01	17.58*	3719.9	2205	N/A	33	.34
U.S.A.	USA	7.68	14.66	0.04*	-3.00*	70.18*	5081.8	7770	N/A	72	.82
Emerging Asian Markets:											
India	IND	5.28	24.88	0.26*	.54*	21.99*	127.5	7000	30	65	1.25
Korea	KOR	11.04	18.92	0.01	.44*	4.34*	191.8	699	12	61	.61
Malaysia	MAL	-38.88	15.84	0.22*	-.76*	14.28*	199.3	478	12	25	1.40
Philippines	PHI	10.32	28.49	-0.01	4.58*	218.38*	55.5	189	38	14	1.50
Taiwan	TAI	15.36	31.10	0.05*	.74*	13.78*	247.3	313	22	430	.15
Thailand	THA	13.68	20.87	0.13*	-.12*	13.73*	131.5	389	24	93	.50
Emerging Latin American Markets:											
Argentina	ARG	-698.88	163.34	0.90*	-4.98*	30.55*	36.9	156	68	34	.16
Brazil	BRA	-497.76	85.68	0.64*	-1.74	6.00*	189.3	544	44	24	.50
Chile	CHI	13.20	15.30	0.23*	.47	11.07*	68.2	279	54	6	2.00
Mexico	MEX	52.56	35.16	0.21*	.83	27.15*	130.2	206	49	50	1.80

Notes:

1 * indicates significance at the 5% level.

2 Market Capitalization, number of listed firms, market turnover ratio, and share of ten largest IFCG index stocks to market capitalization by year-end 1995 from IFC, Emerging Market Fact Book, 1995.

3 Daily average times 240.

4 Square root of variance of daily returns times 240.

5 Rhee, Chang, and Ageloff (1990) provide trading costs for Japan, Korea, Malaysia, Thailand, and Taiwan, including broker fees and taxes. Price (1994) provides the costs in Argentina (excludes fees and taxes). Birinyi Associates provide costs for India and the Philippines. Costs for Brazil (excludes fees and taxes), Chile, and Mexico are provided by the individual local exchanges. The costs for trading in the U.S. are the 1996 costs of trading with discount broker Charles Schwab.

TABLE 2

Mean inflation-adjusted daily returns (%) of buy and sell signals generated by variable moving average (VMA) trading rules. Rules are defined as "(short, long, standard deviation)" where short and long represent the moving average length in days, and the standard deviation is the trading band of 0 standard deviations of each country's return series. The significant p-values at the 5% level are highlighted.

	JAP	USA	IND	KOR	MAL	PHI	TAI	THA	ARG	BRA	CHI	MEX
(1,50,0) buy	0.035	0.030	0.047	0.043	0.058	0.065	0.110	0.075	0.005	0.058	0.041	0.146
sell	0.033	0.038	0.050	0.033	-0.031	-0.049	0.043	0.004	-0.022	-0.007	0.005	0.016
p-value	0.483	0.415	0.473	0.396	**0.012**	**0.004**	**0.050**	**0.046**	0.279	0.074	0.190	**0.001**
(1,150,0) buy	0.025	0.031	0.054	0.047	0.046	0.053	0.092	0.102	0.005	0.022	0.089	0.121
sell	0.030	0.052	0.075	0.020	-0.010	0.001	0.036	-0.018	-0.022	-0.003	0.025	-0.007
p-value	0.457	0.314	0.322	0.274	0.101	0.148	0.114	**0.005**	0.298	0.304	0.078	**0.003**
(5,150,0) buy	0.050	0.035	0.076	0.055	0.034	0.047	0.120	0.128	0.010	-0.018	0.071	0.076
sell	0.008	0.052	0.045	0.017	-0.002	0.018	0.012	-0.042	-0.032	0.028	0.047	0.044
p-value	0.186	0.351	0.251	0.197	0.207	0.280	**0.011**	**0.000**	0.209	0.180	0.304	0.245
(1,200,0) buy	0.040	0.020	0.032	0.038	0.069	0.049	0.114	0.103	0.037	0.021	0.074	0.123
sell	0.015	0.067	0.071	0.031	-0.008	0.017	0.044	0.001	-0.032	-0.018	0.041	0.001
p-value	0.304	0.150	0.207	0.437	0.052	0.273	0.084	**0.021**	0.105	0.237	0.252	**0.006**
(2,200,0) buy	0.077	0.038	0.077	0.085	0.066	0.055	0.136	0.092	0.023	0.012	0.079	0.106
sell	-0.018	0.044	0.021	-0.005	-0.011	0.017	0.018	0.014	-0.023	-0.008	0.038	0.008
p-value	**0.027**	0.447	0.123	**0.025**	0.056	0.235	**0.009**	0.059	0.201	0.357	0.204	**0.021**

TABLE 3

Mean inflation-adjusted daily returns (%) of buy and sell signals generated by variable moving average (VMA) trading rules. Rules are defined as "(short, long, standard deviation)" where short and long represent the moving average length in days, and the standard deviation is the trading band of 1 standard deviation of each country's return series. The significant p-values at the 5% level are highlighted.

	JAP	USA	IND	KOR	MAL	PHI	TAI	THA	ARG	BRA	CHI	MEX
(1,50,1) buy	0.021	0.061	0.045	0.093	0.029	0.120	0.141	-0.399	-0.148	0.094	0.006	0.187
sell	0.033	0.038	0.051	0.033	-0.032	-0.049	0.043	0.003	-0.022	-0.007	0.005	0.016
p-value	0.412	0.311	0.463	0.124	0.122	0.001	0.049	0.009	0.035	0.034	0.497	0.002
(1,150,1) buy	0.029	0.029	0.063	0.059	0.014	0.051	0.118	0.034	-0.038	0.014	0.064	0.106
sell	0.020	0.099	0.181	0.078	-0.015	-0.068	0.020	-0.002	0.078	-0.052	0.114	0.042
p-value	0.448	0.144	0.048	0.377	0.343	0.083	0.096	0.430	0.166	0.166	0.247	0.237
(5,150,1) buy	-0.031	0.003	0.057	0.038	0.043	0.086	0.023	-0.090	0.014	0.001	0.051	0.038
sell	0.033	-0.015	0.201	0.145	-0.123	-0.202	0.109	0.937	0.628	-0.015	-0.132	-0.125
p-value	0.323	0.465	0.157	0.306	0.164	0.029	0.189	0.153	0.122	0.453	0.217	0.101
(1,200,1) buy	0.032	0.008	0.068	0.057	0.024	0.067	0.152	0.034	-0.013	0.008	0.075	0.097
sell	0.031	0.121	0.145	0.061	-0.026	-0.038	0.020	-0.002	0.078	-0.022	0.098	-0.074
p-value	0.498	0.047	0.146	0.477	0.230	0.117	0.040	0.430	0.241	0.335	0.391	0.033
(2,200,1) buy	0.017	0.000	0.063	0.044	0.070	0.053	0.112	-0.060	-0.040	-0.001	0.054	0.117
sell	-0.022	0.049	-0.075	0.097	-0.109	0.024	0.053	0.083	0.110	-0.092	-0.104	-0.031
p-value	0.307	0.300	0.158	0.258	0.026	0.394	0.247	0.310	0.214	0.153	0.108	0.078

TABLE 4
Summary of VMA trading rule statistics using inflation-adjusted returns and a trading band of 0 standard deviations. January 1982 - April 1995.

	JAP	USA	IND	KOR	MAL	PHI	TAI	THA	ARG	BRA	CHI	MEX
(1,50,0) # trades	1235	1255	1230	1220	1110	1115	1155	1120	1170	1155	1165	1055
# buy signals	1280	1340	1230	1235	1210	1235	1345	1330	1100	1260	1300	1270
# sell signals	1240	1180	1290	1285	1310	1285	1175	1190	1420	1260	1220	1250
Annualized VMA return	9.04%	7.77%	12.50%	11.36%	15.49%	17.56%	31.77%	20.70%	1.33%	15.56%	10.88%	44.09%
Returns less trading cost	-1.09%	3.51%	-2.87%	3.92%	-0.05%	0.83%	30.04%	15.10%	-0.54%	9.78%	-12.42%	25.10%
(1,150,0) # trades	965	980	1040	935	910	960	925	855	910	985	940	910
# buy signals	985	1085	1055	975	975	1015	1080	1070	890	995	1075	985
# sell signals	1035	935	965	1045	1045	1005	940	950	1130	1025	945	1035
Annualized VMA return	6.41%	8.18%	14.51%	12.41%	12.18%	14.09%	25.82%	29.08%	1.19%	5.73%	25.04%	35.27%
Returns less trading cost	-1.50%	4.85%	1.51%	6.71%	-0.56%	-0.31%	24.43%	24.80%	-0.27%	0.80%	6.24%	18.89%
(5,150,0) # trades	395	470	395	315	310	360	285	260	335	425	310	290
# buy signals	960	1045	1055	850	1080	1005	980	1055	910	945	1105	1050
# sell signals	1040	955	945	1150	920	995	1020	945	1090	1055	895	950
Annualized VMA return	13.29%	9.26%	20.81%	14.68%	8.90%	12.36%	35.02%	37.73%	2.47%	-4.47%	19.44%	20.93%
Returns less trading cost	10.05%	7.66%	15.87%	12.76%	4.56%	6.96%	34.60%	36.43%	1.93%	-6.59%	13.24%	15.71%
(1,200,0) # trades	790	875	915	840	780	825	810	770	780	860	825	770
# buy signals	885	955	900	820	910	865	970	950	755	865	965	855
# sell signals	885	815	870	950	860	905	800	820	1015	905	805	915
Annualized VMA return	10.47%	5.05%	8.23%	10.05%	18.74%	13.07%	32.90%	29.36%	9.62%	5.38%	20.31%	36.11%
Returns less trading cost	3.99%	2.07%	-3.20%	4.93%	7.82%	0.69%	31.69%	25.51%	8.37%	1.08%	3.81%	22.25%
(2,200,0) # trades	555	665	555	485	460	505	430	510	580	480	495	535
# buy signals	835	920	880	770	985	855	950	935	795	895	940	895
# sell signals	930	845	885	995	780	910	815	830	970	870	825	870
Annualized VMA return	21.13%	10.05%	21.32%	23.54%	18.00%	14.66%	40.58%	25.98%	5.97%	3.01%	21.81%	30.28%
Returns less trading cost	16.58%	7.79%	14.39%	20.58%	11.56%	7.09%	39.93%	23.43%	5.04%	0.61%	11.91%	20.65%
cost per trade	*0.82%*	*0.34%*	*1.25%*	*0.61%*	*1.40%*	*1.50%*	*0.15%*	*0.50%*	*0.16%*	*0.50%*	*2.00%*	*1.80%*
Average VMA return	*12.07%*	*8.06%*	*15.48%*	*14.41%*	*14.66%*	*14.35%*	*33.22%*	*28.57%*	*4.11%*	*5.04%*	*19.50%*	*33.34%*
VMA return less cost	*5.61%*	*5.18%*	*5.14%*	*9.78%*	*4.66%*	*3.05%*	*32.14%*	*25.05%*	*2.91%*	*1.14%*	*4.56%*	*20.52%*
Buy & Hold Return	*5.90%*	*7.70%*	*14.55%*	*8.63%*	*8.34%*	*9.52%*	*17.59%*	*15.36%*	*32.08%*	*22.91%*	*11.26%*	*19.53%*

TABLE 5

Summary of VMA trading rule statistics using inflation adjusted returns and a trading band of 1 standard deviation. January 1982 - April 1995.

		JAP	USA	IND	KOR	MAL	PHI	TAI	THA	ARG	BRA	CHI	MEX
(1,50,1)	# trades	410	460	350	440	440	390	360	60	320	530	470	365
	# buy signals	465	570	315	475	430	505	480	35	275	655	520	460
	# sell signals	1240	1180	1285	1285	1305	1285	1175	1185	1415	1260	1220	1250
Annualized VMA return		5.34%	16.45%	11.87%	26.02%	7.42%	35.04%	42.42%	-63.11%	-30.92%	26.46%	1.45%	59.78%
Returns less trading cost		1.98%	14.88%	7.49%	23.34%	1.26%	29.19%	41.88%	-63.41%	-31.43%	23.81%	-7.95%	53.21%
(1,150,1)	# trades	280	260	210	280	190	230	250	30	160	300	220	110
	# buy signals	1075	1150	1090	875	1305	1080	780	645	1160	910	1100	615
	# sell signals	275	220	205	360	200	240	300	55	160	360	235	170
Annualized VMA return		7.46%	7.63%	16.94%	15.76%	3.56%	13.68%	34.27%	8.99%	-8.98%	3.66%	17.31%	30.35%
Returns less trading cost		5.16%	6.74%	14.31%	14.05%	0.90%	10.23%	33.89%	8.84%	-9.23%	2.16%	12.91%	28.37%
(5,150,1)	# trades	10	20	30	30	30	20	40	10	20	50	20	10
	# buy signals	210	590	725	1360	1425	795	625	60	1470	1250	850	1200
	# sell signals	105	30	30	35	50	100	140	10	10	80	30	45
Annualized VMA return		-7.43%	0.78%	15.20%	9.98%	11.40%	24.05%	6.04%	-20.19%	3.64%	0.25%	13.50%	10.01%
Returns less trading cost		-7.51%	0.72%	14.83%	9.80%	10.98%	23.75%	5.98%	-20.24%	3.61%	0.00%	13.10%	9.83%
(1,200,1)	# trades	270	250	170	290	190	210	220	30	110	280	180	90
	# buy signals	1065	995	970	745	1110	1155	730	645	905	785	915	520
	# sell signals	265	215	180	370	195	230	300	55	130	330	200	125
Annualized VMA return		8.26%	1.89%	18.39%	15.30%	6.27%	18.14%	46.34%	8.99%	-3.17%	2.00%	20.68%	27.32%
Returns less trading cost		6.05%	1.04%	16.27%	13.53%	3.61%	14.99%	46.01%	8.84%	-3.35%	0.60%	17.08%	25.70%
(2,200,1)	# trades	100	90	50	130	60	110	100	10	40	130	100	20
	# buy signals	515	790	1385	625	815	1135	590	75	1090	860	980	530
	# sell signals	205	120	65	200	145	165	205	45	65	210	100	75
Annualized VMA return		4.46%	0.09%	17.11%	11.60%	19.14%	14.28%	32.38%	-13.96%	-9.59%	-0.20%	14.50%	33.90%
Returns less trading cost		3.64%	-0.22%	16.48%	10.81%	18.30%	12.63%	32.23%	-14.01%	-9.66%	-0.85%	12.50%	33.54%
	cost per trade	*0.82%*	*0.34%*	*1.25%*	*0.61%*	*1.40%*	*1.50%*	*0.15%*	*0.50%*	*0.16%*	*0.50%*	*2.00%*	*1.80%*
	average VMA return	*3.62%*	*5.37%*	*15.90%*	*15.73%*	*9.56%*	*21.04%*	*32.29%*	*-15.86%*	*-9.80%*	*6.43%*	*13.49%*	*32.27%*
	VMA return less cost	*1.86%*	*4.63%*	*13.88%*	*14.31%*	*7.01%*	*18.16%*	*32.00%*	*-16.00%*	*-10.01%*	*5.14%*	*9.53%*	*30.13%*
	Buy & Hold Return	*5.90%*	*7.70%*	*14.55%*	*8.63%*	*8.34%*	*9.52%*	*17.59%*	*15.36%*	*32.08%*	*22.91%*	*11.26%*	*19.53%*