Technical Trading Rules in Emerging Markets and the 1997 Asian Currency Crises

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Abstract

The ability of simple technical trading rules to forecast future stock market movements is considered for 17 emerging markets sampled over the longest period of January, 1986 to September, 2003. Some of the trading rules considered were able to generate significant returns, and this information could be profitably exploited on occasion. Market conditions and trading volume is found to play an important role in determining the usefulness of technical trading rules.

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1. Introduction

The term 'technical analysis' broadly encompasses a wide range of analytical tools and techniques (see Reilly and Brown, 1994), each of which share a common philosophy that the past can be used to predict the future. A large literature has emerged which attempts to identify the accuracy with which these trading rules forecast future movements in stock prices. Developed markets, and in particular the US, have been the primary focus of this research (see Brock, Lakonishok and Le Baron, 1992, Bessembinder and Chan, 1998 and more recently Ready, 2002, Kwon and Kish, 2002a,b, Neely, 2003 and Nam, Washer and Chu, 2005). In general, the evidence suggests that while some trading rules do possess predicative power, this does not necessarily translate into profitable information due to trading costs.[1]

More recently, the focus of technical trading analysis has shifted to emerging stock markets, which collectively provide an important alternative source of opportunities to international investors. Technical trading strategies may prove more successful in this context, as the level of serial correlation in emerging market share prices is typically much higher relative to their developed market counterparts (see Harvey, 1995). For example, a number of studies have applied technical trading rules to a particular Latin American or South East Asian stock market. Parisi and Vasquez (2000) sample data from the Chilean stock market and find that buy signals generate higher returns than sell signals although risk following these signals is not significantly different. Tian, Wan and Guo (2002) focus on the Chinese markets and conclude that simple technical trading rules are profitable after trading costs. Kang, Liu and Ni (2002) also consider a range of trading strategies applied to China 'A' shares and find significant abnormal profits for some momentum strategies. Hameed and Ting (2000) and Lai, Balachandher and Nor (2003) both focus on the Malaysian stock market and find evidence of predictability, which the former attribute to the institutional arrangement of the KLSE.

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[1] The ability of technical trading strategies to predict future returns has two possible interpretations: capital markets are inefficient (resulting from herding behaviour or the irrational reaction of stock prices to news) or equilibrium expected returns are time varying (see Ferson, 1995 for a review of conditional asset pricing models). Ito (1999) directly tests the latter implication and finds that some equilibrium asset pricing models are consistent with the technical trading returns generated for a number of countries in the data set.

More generally, the South East Asian Region has been the focus of a number of studies. Ahmed, Beck and Goldreyer (2000) find evidence of significant profits to variable moving average rules in three Asian markets. Hameed and Kusnadi (2002) study six Asian stock markets and conclude that the factors which drive momentum in the US are not prevalent in Asian markets. For the Indian market, Gunasekarage and Power (2001) examine the Bombay, Colombo, Dhaka and Karachi stock exchanges and conclude that technical trading rules have predictive power.

A recent research trend has been toward studies which consider a range of markets from around the world. Ito (1999) finds evidence of significant forecast power for a range of technical rules applied to Indonesia, Mexico and Taiwan. Ratner and Leal (1999) concluded that the majority of the trading rules considered had predictive power in their study technical trading rules in four Latin American and six Asian stock markets. Chang, Lima and Tabak (2004) consider the same sample of countries, with the addition of Indonesia and reach a similar conclusion. Chan, Hameed and Tong (2000) focus on 23 markets of which five are developing countries in South East Asia and find further evidence of significant profits to momentum strategies which they attribute to predictability in market indices.

The aim of this paper is to provide further evidence on the predictive ability of three general classes of technical trading rule: the Variable Length Moving Average, Fixed Length Moving Average and Trade Range Breakout. These three rules have proven to be most popular in the literature and their use will allow direct comparisons to previous research. The dataset in this study consists of a broad cross section of 17 Latin American and Asian emerging markets. Most previous studies have typically focused on, at best, a few emerging market stock exchanges. Thus, rather than considering one or a small subset of markets, this study will be able to simultaneously assess the evidence on the predictive ability of trading rules across a broad subset of the emerging markets sector.

The previous literature has focussed primarily on the pre-1997 currency crises period, which for many emerging markets was characterised by a strong upward trend in prices. Such market trends have been shown to influence the nature and success of trading signals (see Fernandez-Rodriguez, Gonzalez-Martel and Sosvilla-Rivero, 2000, Mills, 1997, Chan, Hameed and Tong, 2000 and Parisi and Vasquez, 2000). This study will use data taken from a sample period which transcends both the bull market pre-crises period and the turbulent post-crises era. As such, the results will provide insights into the influence of the general market conditions on the forecasting ability of trading signals. It is expected that the turmoil following the currency crisis reduced the persistence in market trends with obvious implications for the success of momentum based trading strategies. A further contribution of this paper is to contrast the two different methods for assessing the significance of the returns to trading strategies. Many papers have focused on t-statistic based tests of significance which may not be appropriate in the current context and bootstrapping is frequently considered as an alternative. In this paper, both techniques are considered and their impact on the significance of the results established. Finally, this paper provides some observations on the influence of trading volume on the forecasting ability of these technical trading rules and also comments on whether or not the information provided by these rules can be used profitably.

Thus, this paper will consolidate past research on the use of technical trading strategies in emerging markets as well as provide additional evidence from a number of previously untested markets. Further, what causes the differences in forecasting ability is also considered. The remainder of this paper is structured as follows. Section 2 details the three main classes of trading rule considered in this paper. Section 3 introduces the data and presents the results for each of the VMA, FMA and TRB rules applied to this data. Section 4 presents a summary of these results and some concluding comments.

2 Technical Trading Rules

An extensive family of technical trading strategies exist which Reilly and Brown (1994) classify as: i - contrary opinion rules; ii - follow the smart money rules; iii - other market environment indicators; and iv - stock price and volume techniques. In this paper, only rules belonging to the final grouping are to be considered since they collectively represent the most widely tested group of technical trading rules. More specifically, this study shall limit its focus to consider three of the most popular rules:

the Variable Length Moving Average (VMA), the Fixed Length Moving Average (FMA) and the Trading Range Breakout (TRB).

The VMA and the FMA both base their trading decisions on the movements of a short term moving average of prices (SMA) relative to a long term moving average of prices (LMA). The period over which these moving averages are estimated is important as it is necessary to select a period which is will filter out noise from the data, yet remain sensitive enough to indicate the initiation of a price tend. When the SMA crosses above the LMA, a buy signal is generated and vice versa for a sell signal. More formally, the VMA generates trading signals according to the following rules:

$$\frac{\sum_{sma=1}^{SMA} P_{i,sma}}{SMA} > \frac{\sum_{lma=1}^{LMA} P_{i,lma}}{LMA} + T = BUY \tag{1}$$

$$\frac{\sum_{sma=1}^{SMA} P_{i,sma}}{SMA} < \frac{\sum_{lma=1}^{LMA} P_{i,lma}}{LMA} + T = SELL \tag{2}$$

where P_i is the daily stock index series for market *i*, T is the threshold which is set equal to one standard deviation of the return series, and SMA and LMA are the short and long term moving average periods.

A variation on this rule employs an additional filter such that the SMA must move above or below the LMA by some predetermined amount. The use of a band eliminates spurious trading signals which are generated when the two moving averages are close to each other and cross frequently. In this case, a trading signal is generated where the SMA breaches either the upper or lower boundary set by this filter which Brock et al (1992) set equal to 1%. Bessembinder and Chan (1995) argue that the large differences in volatility in emerging markets necessitate a band width specific to each series. As such, in this paper a bandwidth is specified which is equal to one standard deviation of the return series.

Once a signal is generated, the investor is assumed to take the appropriate position in the market with a resultant rate of return equal to the movement of the market in the following period. The FMA trading rule requires investors to hold their position in the market for a predetermined period of time during which all subsequent signals are ignored. At the end of that fixed-length holding period, the investor re-enters the market in an appropriate fashion as dictated by the next trading signal received. In this paper, a third holding period option is explored. Under this rule, a trading signal results in an investor taking a position in the market until a contrary signal is received. Thus, the holding period varies contingent on the time between signals and the estimated return is the movement in the market over that period.[2]

In this paper, the VMA and FMA rules are estimated using the following values (1,50), (1,150), (5,150), (1,200) and (2,200) where the first term denotes the SMA and the second term indicates the LMA. A threshold of either zero or 1σ is assumed for each trading rule combination which is indicated by either a 0 or a T following the designation of the SMA and LMA. Following Brock et al (1992), 10 day holding periods are assumed for the FMA.

A third form of trading rule considered in this paper is the TRB rule. A trading range has an upper and lower limit which is set by the recent maximum and minimum of prices. If the current price breaches a boundary, it is assumed that a trend has been initiated and a trading signal is generated. More specifically, if the current price exceeds the upper limit, a buy signal is generated and a breach of the lower limit creates a sell signal. More formally:

$$P_{i,t} > Max\left[P_{i,t-1},\ldots,P_{i,t-n}\right] + T = BUY \tag{3}$$

$$P_{i,t} < Min\left[P_{i,t-1},\ldots,P_{i,t-n}\right] + T = SELL \tag{4}$$

where *n* is the number of days over which the trading range is set which is assumed to take values of 50, 150 or 200 days. To limit the occurrence of spurious signals, the decision rule may be modified to include a threshold term equal to one standard deviation of market returns.

[2] The performance of this third type of holding period is qualitatively similar to the FMA and as such, these results are omitted to conserve space.

Similar to the VMA and FMA rules, once a trading signal is generated, the investor is assumed to take an appropriate position in the market and earns the return in the next period. Alternatively, if a fixed holding period is assumed, all subsequent trading signals are ignored and the investor earns the return observed over that period. After the completion of this trade, the investor than re-enters the market on receiving a new trading signal. A third possibility is the investor holds their position until a contrary signal is received and earns are return equal to the movement of the market over this period.[3]

3. The Ability of Trading Rules to Forecast Future Price Movements

3.1 VMA Trading Signals

Daily local currency[4] market index data was sourced from Datastream for 17 countries which are classified as emerging[5] over a maximum period of January, 1986 to September, 2003. A Datastream US market index is also included to provide a benchmark against which the results for these developing countries may be compared. A list of these countries, the number of observations and descriptive statistics for the data are provided in Table 1. The stock index price series for Argentina exhibits the highest average daily return (0.0026) and also the largest one day rise (0.3760), fall (-0.6076) and the greatest dispersion of observations (0.0341). India, Malaysia and Venezuela also produced evidence of large one day returns as their maximum return in the sample period exceeding 20%. Turkey recorded the second highest mean (0.0019) and standard deviation (0.0291) of returns although Korea (0.0201), Poland (0.0206), Taiwan (0.0211), and Venezuela (0.0233) exhibited similar market levels of market volatility. Fourteen of the series were positively skewed and all of the returns data fails the Jarque-Bera test for normality. Thus, the emerging markets sampled in

[3] The performance of the TRB rule assuming a 10 day holding period and sequential trading signals does not add to the discussion and were omitted to conserve space.

[4] Alternatively, US dollar indices could have been specified which are arguably more relevant for international investors who are concerned only with home currency returns. The use of such indices however, introduces an additional element to the analysis insomuch as the trading rules would be trying to capture momentum in both the stock market and the exchange rate. The literature has tended to focus on these two issues separately. For readers who are interested in the forecasting ability of technical trading strategies in foreign exchange markets see, inter alia Sosvilla-Rivero, Andrada-Felix and Fernandez-Rodriguez (2002) Gencay, Dacorogna, Olsen and Pictet (2003), Neely and Weller (2003) and Ahmed, Beck and Goldreyer (2005).

[5] Standard and Poors Stock Market Factbook, 2003.

this study exhibit evidence of higher risk and returns which is consistent with Harvey (1995).

[Table 1 here]

Table 2 reports the results of the VMA(1,50,0) trading rule applied to these national stock market index data. For the sample of emerging markets, with the exception of Korea, each country generated more buy signals than sell signals which is consistent with an upward trending market. In some cases, such as Argentina, Chile and Mexico, the difference was quite pronounced and over 50% more buy signals were observed than sell signals. The mean stock market return following a buy signal was positive in every case. Following Chang, Lima and Tabak (2004), the statistical significance of these buy (sell) signals may be assessed using the following t-statistic:

$$\frac{\mu_r - \mu}{\left(\sigma^2 / N + \sigma_r^2 / N_r\right)^{1/2}} \tag{5}$$

where N_r is the number of buy (sell) signals, N is the number of observations, μ_r is the mean return following a buy (sell) signal, and μ is the unconditional mean and σ^2 is the unconditional variance. The t-statistic for these mean returns following a buy signal is significantly greater than the average return for 11 of these emerging markets at the 5% level, and all countries at the 10% level, except for Brazil, Mexico and Turkey. The mean sell signal was negative and significant for 13 countries at the 5% level and all countries except for Brazil and Turkey at the 10% level. The spread is the difference between the mean return following a buy signal and a sell signal and its statistical significance may be estimated as:

$$\frac{\mu_B - \mu_S}{\left(\sigma_B^2 / N_B + \sigma_S^2 / N_S\right)^{1/2}} \tag{6}$$

where μ_B (μ_S) is the mean return following a buy (sell) signal and N_B (N_S) is the number of signals indicating a buy (sell). The spread and the associated t-statistic are presented in Table 2 and in every case it is significantly different from zero.

[Table 2 here]

The market volatility following buy and sell signals may be assessed by considering the standard deviation of the observed returns. Except for Argentina and Colombia, the standard deviation of returns following sell signals are relatively higher compared to the equivalent figure following a buy signal. The final two columns of Table 2 presents information on the percentage of returns following a buy (sell) signal which are positive (negative). Under the null hypothesis of market efficiency, the fraction of positive returns should be the same for each type of trading signal. This technical trading rule however, produces useful signals as this percentage is only equal to 50 in the case of buy signals for Indonesia.

By way of comparison, the final row of Table 2 presents the equivalent results for US stock market returns data which is included in this study as a developed market benchmark. The US series generated more buy signals than any other market and an average number of sell signals. The average return on a buy (sell) signal is actually below (above) the average return for the sample as indicated by the negative (positive) signs on the t–statistics and both are insignificant as is the spread. The standard deviation of returns following a buy signal is the lowest estimated and the US volatility estimate following a sell signal is one of the lowest in the sample. These results are typical of those found in the previous literature (see Ito, 1999 and Ratner and Leal, 1999) where low autocorrelations and poor trading rule performance are the norm for developed markets.

Beyond the VMA(1,50), it is possible to consider the forecasting ability of other SMA and LMA values. Following Brock et al (1992), the following VMA rules were also tested: (1,150), (5,150), (1,200) and (2,200) with and without a threshold value.[6] Individual results are not presented to conserve space, however a summary of the output for these VMA rules is presented in Table 3. This summary presents the average value taken across the spectrum of VMA trading rules tested except for the t-statistics which is a count of the number of significant t-scores for the mean buy/sell

[6] Ratner and Leal (1999) argue that a signal should be followed by a one period lag to allow for the effects of nonsynchronous trading. The analysis of this paper was replicated assuming such a lag and the results are not qualitatively different from those presented and are available on request.

return as well as the spread. The number of trading signals generated by each of the VMA rules associated with different SMA and LMA values do not differ substantially. The use of a threshold term however, does reduce the number of trading signals by an average of 13.4%. The minimum is 4.4% fewer buy signals for the (1,200) rule applied to Malaysia and the maximum is 40.6% fewer sell signals for Argentina using the (1,50) rule.

[Table 3 here]

The mean return following a buy signal was greater than the sample mean in every instance although the extent to which this difference was significant varied throughout the sample. In the case of Argentina, six of the ten VMA rules generated a mean buy return significantly greater than the average return. For Brazil and Turkey, none of the buy trading signals produced returns which were significantly different from the mean sample return. The sell signals produced a more mixed set of results. In the case of Argentina and Chile, nine of the ten rules tested produced sell signals which resulted in average returns which are significantly less than the sample average return. For Brazil, Mexico and Turkey however, none of the trading rules produced sell signals which forecast future returns. Further, in the case of Korea, Mexico and Poland, only one trading rule successfully forecast future returns on average. The spread between the returns to buy and sell signals was significantly different for all of the rules tested for Argentina, Chile, Colombia, Malaysia, the Philippines and Taiwan. Consistent with this evidence, Parisi and Vasquez (2000) found nine of ten spreads to be significant for their analysis of Chile. Similarly, while nine of ten spreads for India were significant in Table 3, all of the spreads in Gunasekarage and Power (2001) were significant at the 10% level. The risk of buy signals is less than the risk associated with sell signals for fourteen countries. By way of comparison, the benchmark results for the US mirror that of the VMA(1,50) rule insomuch as none of the trading rules generated a significant t-statistic and the spread was insignificant.

Consistent with Ratner and Leal (1999), the results of this study suggest that the success of technical trading rules is country specific as for some cases nearly all of the trading rules produced significant spreads while for others, relatively few of the spreads are significant. What determines the success or otherwise of these technical strategies is an issue to be addressed later in this paper.

3.2 TRB and FMA Trading Rules

The standard set of VMA rules considered in section 3.1 classify every day as a trading day. An alternative approach is to assume that the investor enters the market on receiving a signal and holds that position for a fixed period of time during which all other signals are ignored. At the end of this period, the investor waits for the next trading signal and so on for the duration of the sample period. This is a FMA trading rule and following Brock et al (1992), the holding period is set at 10 days.[7] Detailed results for the spectrum of FMA trading rules considered are not presented to conserve space however, a summary of the different trading rules for each country is presented in Table 4. The number of trading signals is approximately 10% of the number of VMA trading signals which is to be expected as a new trade is undertaken virtually every 10 days. Where every day is classified as a buy or a sell day, a new trading signal is received as soon as the 10 day holding period finishes. Where a threshold is specified, a new trading signal may not be immediately available depending on the machinations of the market. The delay, however, would only be minimal in particular where a SMA of only a day or two is specified.

[Table 4 here]

The mean returns on buy and sell signals for the FMA rules reveal that only a handful of the trading rules tested were successful. Most of the buy signals did not generate positive returns which were significantly different to the average return for the sample period. Except for Argentina, Chile and the Philippines, most of the sell signals also failed to correctly predict the movements of the market. Compared to the VMA rules, the TRB rules do not generate as many significant returns however, if a 10% level of significance is specified the results are more comparable. For example, in the case of Argentina, six (nine) of the trading rules generated buy signals which were

[7] A fifty day holding period is also tested and the results were not qualitatively different from those presented.

significantly greater (less) than the average return at the 10% level. Further, the spreads between the buy and sell are significant across all ten trading rules in all ten case for Argentina (and Chile). Further, for India, Malaysia, Philippines and Taiwan, six of the spreads are significantly different at the 5% level. The volatility of the market following TRB generated buy signals is lower than following sell signals in the majority of cases. Further, the volatility following both buy and sell signals is lower in the US market compared to these emerging economies. By way of comparison to the VMA rules, 34.1% of the 85 different FMA rules tested produced a significant spread which is less than the 52.1% success rate of the VMA rules.

The TRB rules are based on a similar philosophy to the VMA and FMA rules insomuch as they attempt to identify the start of a trend in the movement of prices. The main difference is that the TRB rule focuses on the movement of the current price relative to a band of recent high and low prices rather than a long term moving average of recent prices. In this paper, band lengths of 50, 150 and 200 days were tested and a summary of the results for each country is presented in Table 5. As the TRB benchmarks a band of recent high and low prices, even in the absence of a threshold, each day may not necessarily generate a trading signal where the current price resides with the bounds of the current band. Thus, a TRB rule will generate fewer signals compared to a VMA rules and the estimated results are consistent with this notion. The mean returns indicate that the buy signals generated were generally successful in predicting the future market movements except for Korea and Poland. The TRB rules were relatively less successful in generating sell signals as at least half of the rules tested were insignificant in eight of the emerging markets tested. The spread was significant for 76.5% of all of the TRB strategies tested and in 12 of the countries considered, the spread was significant for all six TRB rules. Consistent with the VMA and FMA rules, the volatility of the market following sell signals was greater than that following buy signals in the majority of cases. The TRB applied to the US stock market data failed to generate a significant buy or sell signal return.

These results for the TRB suggests that they are more successful in identifying future movements in the market which is consistent with other studies which have focussed on VMA and TRB strategies (for example Parisi and Vasquez, 2000) and suggests that other studies which limit their focus solely to the VMA and FMA rules exclude a potentially superior trading strategy (such as Ratner and Leal, 1999 and Gunasekarage and Power, 2001).

[Table 5 here]

3.3 Bootstrap Tests

To establish the statistical significance of the returns to a technical trading strategy, many papers use the t-statistic based measures as specified in equations 5 and 6 (see, inter alia, Parisi and Vasquez, 2000 and Gunasekarage and Power, 2001). Stock returns are characterised by the presence of non-normality and time dependence however, which violates the underlying assumptions of these tests. Brock et al (1992) suggest the use of bootstrapping as an alternative means of testing the significance of returns.[8] A number of different bootstrap techniques have been used in the literature to test the significance of the returns. In this paper, the method of Bessembinder and Chan (1998) is adopted, which is a procedure very similar to the original bootstrap method of Brock et al (1992). In brief, the actual set of returns is sampled with replacement, a simulated price index series constructed and the range of trading strategies applied to this data. The process is repeated 500 times, which Ratner and Leal (1999) argue is a sufficient number of trials. The bootstrap p-value is the proportion of simulation outcomes which exceed the actual sample estimate. For full details of this procedure and a discussion of the computation of bootstrap p-values, refer to the Appendix of Bessembinder and Chan (1998).

Table 2 presents the bootstrap p-values in parentheses after the respective t-values for the VMA(1,50,0) rule. A p-value of <0.05 rejects the null hypothesis the returns are equal to zero. As reported earlier, the t-statistic for these mean returns is significant for all countries at the 10% level, except for Brazil, Mexico and Turkey. The bootstrap p-values suggests that all of the estimated mean returns are significant at the 10% level except for Brazil. The same pattern emerges for the sell signals which are all highly significant as the p-value is less than 0.05 in each case. For the US market, the p-value for the mean buy and sell return as well as the spread is insignificant which is also consistent with the t-values.

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[8] For a survey of bootstrapping see Ruiz and Pascual (2002).

In the context of all of the trading signals considered (Tables 3, 4 and 5), the number of significant p-values is presented in parentheses after the number of significant t-statistics. For example, from Table 3, six of the ten VMA rules applied to the Argentinean stock market data generated a significant t-statistic. Nine of these rules however, generated a significant p-value. In general, the bootstrap p-values tend to mirror the results of the t-statistics and any differences tend reflect a tendency of the bootstrap p-values to reject the null hypothesis more often. This is to be expected, as the t-statistics test whether the mean return is greater than the sample mean rather than the p-value which tests against a null of no forecast power. In some cases, this difference can be quite marked. For example, the VMA trading rules applied to Chile (Table 3) generated a significant buy signal return in only three cases according to the t-test, however the p-value rejected the null in all ten cases. Closer inspection of the t-statistics explains this apparent anomaly, as nine of the VMA rules were significant at the 10% level. The use of a bootstrap p-value, with its less restrictive null, is sufficient to generate a large change in the number of significant trading rules. Given the similarities between these two techniques, the remainder of the paper will focus on the t-statistic based tests of significance.

3.4 The Profitability and Performance of Technical Trading Strategies

The preceding analysis has focused on the ability of technical trading rules to forecast stock market movements. Clear evidence is found to suggest that technical rules do have some predictive ability for emerging markets in the form of significant positive returns to buy signals and negative returns to sell signals. By way of contrast, the results for the US market suggest that these rules have no such predictive ability which is typical of the literature which has considered developed markets.

Further insights into the informational advantage offered by these technical trading strategies can be garnered by comparing the net return to a trading rule to the returns to a passive strategy, such as the buy and hold over the entire sample period. To this end, the first column in Panel A of Table 6 presents the returns to a buy and hold strategy in the sample of emerging markets for the sample period. Argentina was the best performing of the emerging markets considered and rose by 1074.65%. Poland was the worst performing country with a negative share market return of –15.09% over the sample period. The US market return is 165.55%, which is close to the median emerging market return. These buy and hold returns may be compared to a simple estimate of the return to a technical trading strategy, which may be calculated by summing the product of the average return to each signal type and the number of signals generated. For example, the second column of Panel A presents the whole period return to a portfolio which is traded according to the signals generated by a VMA(1,50,0) strategy. For all markets considered except Turkey and Mexico, the VMA provided a return which exceeded the buy-hold return. This suggests that the trading signal is generating useful information. In the case of Indonesia, the difference was 500% as the buy-hold strategy yielded a loss of 12.70%, whereas the VMA rule provided a return of 520.65%. For the US market, the VMA rule performed poorly and the performance is -2.22% compared to a buy-hold return of 165.55%. These results are typical of those generated for the entire spectrum of trading strategies considered in this paper.

[Table 6 here]

It is an interesting question to consider what factors may determine the ability of these technical trading rules to predict stock market returns. A limited number of previous studies have considered this question in the context of an individual country. For example, Kang, Liu and Ni (2002) argue the Chinese stock market is unique because of the extent of government regulations and the investor composition. Hameed and Ting (2000) attribute price patterns to institutional arrangements on the Malaysian stock exchange. More generally, the success of technical trading strategies is dependent on the degree of persistence of market trends. As has already been discussed, emerging markets exhibit greater autocorrelation compared to developed markets. As such, the literature which focuses on the determinants of autocorrelation may be of some use in answering this question. A survey of the literature on this issue, reveals that trading volume is commonly thought to influence the level of autocorrelation through reduced nonsynchronicity of prices (see McKenzie and Faff, 2005). Empirical testing however, suggests that actual autocorrelation estimates are significantly greater than those implied by thin trading alone (Lo and MacKinlay, 1990). An alternative explanation for the relationship between autocorrelation and trading volume focuses on the presence of informed traders in the market (see Campbell, Grossman and Wang, 1993). When viewed as an information proxy, low trading volume, implies an absence of news and, hence, a relative absence of informed traders. As such, naive traders are expected to be most prominent during quiet trading periods (using information predominantly embodied in past returns), thereby inducing autocorrelation in stock returns. Accepting either of these explanations, the success of technical trading strategies may be a function of market depth.

Panel B of Table 6 presents 2002 market turnover information for each of the countries considered in this study, which is reasonable a proxy for market depth and has the added benefit of being directly comparable across countries. Both Taiwan and Korea both have turnover ratios that are higher than that of the US, and India has a turnover ratio which is comparable. At the other end of the spectrum, the turnover ratios of Argentina, Chile, Colombia, Peru, the Philippines and Venezuela are all extremely low. As a simple rule of thumb, if more than half the buy and/or sell trading rules generated a significant p-value, the technical trading strategies are argued to have performed relatively better for that country. According to this criterion, the VMA and FMA[9] technical trading strategies were more successful for Argentina, Chile, Colombia, India, Malaysia, Peru, the Philippines, Taiwan and Venezuela. With the exception of India, Malaysia and Taiwan, these are the same group of countries which were previously identified as having very low turnover ratios. Thus, market depth would appear to exert some influence on the ability of technical trading strategies to forecast future price movements, which is consistent with expectations. This is only part of the story however, as both India and Taiwan both have very high trading volume. These factors are most likely institutional (Hameed and Ting, 2000, suggest this is the case for Malaysia) and more detailed analysis would require an in depth study of each market which is beyond the scope of this paper.[10] The author commends this as an area for further research.

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[9] The TRB is not considered as it was 'successful' across most of the countries considered.
[10] Swan and Westerholm (2003) provide details on the institutional features and trading architecture of a large number of stock exchanges.

A further question considered in this paper is whether the informational advantage offered by these technical strategies translates into profitable trading opportunities. The estimated returns discussed in this paper may be appropriately termed pre-cost trading returns and should not be confused with profits, which are net of transaction costs. To establish whether these rules generate profitable trading opportunities, information as to the cost of execution is necessary. The wide range of markets considered in this paper, means it is difficult to provide detailed information on the cost of trading on each exchange. This issue is further hampered by issues such as whether it is local or foreign investors trading costs which are relevant, should explicit and implicit costs be considered, and so on.

The literature provides some guidance on the issue of trading costs in stock markets. For example, Domowitz, Glen and Mahavan (2001) use the Elkin/McSherry database to calculate average one-way trading costs over the period 1996 – 1998.[11] Chakravarty, Chiyachantana and Jiang (2004) use institutional trading data sourced from the Plexus Group to estimate one-way percentage trading costs in 35 foreign countries. Swan and Westerholm (2005) derive round trip percentage trading cost estimates for 33 exchanges. Panel C of Table 6 presents the estimated explicit[12] trading costs for each exchange included in this study as reported in each of these three papers as well as the Elkin/McSherry trading cost estimates for 2002.

It is interesting to note that these different sources of trading cost information do not rank the markets consistently. For example, the Philippines (Venezuela, Peru) has the highest trading costs according to the Domowitz (Chakravarty, Swan respectively) estimates. Domowitz and Swan both rank India as the cheapest market to trade in, while Chakravarty ranks Turkey as the cheapest. These differences are not surprising and most probably only serve to highlight the substantial difficulties in constructing this type of information. It is also interesting to note that all three databases suggest that emerging markets are not necessarily more expensive to trade in relative to

[11] Ito (1999) also has Elkins/McSherry trading cost information for a limited sample of four countries.
[12] Implicit trading costs are ignored to make the cost estimates provided by each paper as comparable as possible. These costs are typically quite small relative to the explicit trading costs and as such, their omission is unlikely to significantly alter the tenor of the results.

developed markets. In each database, a number of markets possess lower explicit trading costs relative to the US.

Comparing the Domowitz 1996 – 1998 average cost estimates to the Elkin/McSherry 2002 data allows a comparison of trading costs over time. It is interesting to note that the ranking of each exchange by cost has changed in some cases quite markedly. For example, Chile went from being the fifth cheapest exchange in the Domowitz sample to the second most expensive exchange in 2002. Colombia and India are two other exchanges that became notably more expensive during this period relative to the other markets. Venezuela was the only exchange which was noteworthy for lowering its trading costs. In the Domowitz sample, Venezuela was the second most expensive market in which to trade, yet by 2002 it had fallen to the eighth most expensive exchange.

Comparing the average return to each trading signal in Tables 3, 4 and 5 to these trading cost estimates and for the VMA series of rules, it is clear that in the majority of cases, the positive returns to each trading signal are absorbed by trading costs. This is to be expected since the VMA rule by construction effectively assumes the trader takes a position at market opening each day in the case of the zero threshold signal. The FMA results provide evidence of profitable trading opportunities in the case of buy signals for Argentina, India and Mexico, sell signals in the case of China and both buy and sell signals in the case of Taiwan and Turkey. In each case, the average return to the signal exceeded the round trip trading costs (estimated as twice the one-way cost estimate provided or the actual two-way cost estimate in the case of the Swan and Westerholm data). Further evidence of profitable trading opportunities are found for the TRB buy signals generated for Argentina, Turkey and Venezuela. While concerns over data snooping (see Sullivan, Timmermann and White, 1999) suggest these results must be interpreted with caution, they nonetheless provide evidence that trading costs do not necessarily account for all of the excess returns generated by technical trading signals.

3.5 Technical Trading Rules and the 1997 Currency Crises

The previous literature on technical trading and emerging markets has typically considered data sampled prior to 1997. This was a period in which the emerging markets sector, and in particular those countries located in South-East Asia, experienced unprecedented economic growth and financial prosperity. The Asian currency crisis however, marked the onset of widespread economic turmoil across the emerging markets sector resulting in significant share market falls and wiping billions of dollars from market capitalisation. The general nature and direction of movements in the market have been found to influence the nature and success of technical trading strategies (see Fernandez-Rodriguez et al., 2000, Mills, 1997 and Parisi and Vasquez, 2000) and it is an interesting empirical question to consider the influence of the Asian currency crises on the success of technical trading strategies. To complete this analysis, it is necessary to define a date on which the crises started and July 2, 1997 is chosen, which is the date on which Thailand floated the baht. Although this choice is somewhat subjective – some stock markets began to decline prior to this period, quite possibly in anticipation of the forthcoming events, while others fell after this date as a result of contagion – it is argued that this date represents a reasonable starting point given the wide range of countries considered in this study.

A buy and hold strategy in the pre-crisis subperiod would have generated positive returns in excess of 1000% in the case of Argentina (Poland is the only country in which the market index fell in the pre-crises period). Following July 1997 however, emerging stock markets fall into one of three categories. The first group consists of Thailand, Malaysia and the Philippines, which have yet to fully recover from the currency crises and the market index to the end of the sample period is characterised by a general downward trend. The second group are those Asian markets which fell immediately after the crises, but have since recovered to pre-crisis levels. Finally, there are the non-Asian emerging markets, whose stock markets fell as a result of contagion.

The forecasting ability of technical trading strategies in a pre- and post-currency crises period may be established by applying the VMA, FMA and TRB rules to two subperiods defined by the date July 2, 1997. A summary of the data in each subperiod is presented in Table 7 and significant autocorrelation is found in both subperiods for all of the emerging markets except Korea, Malaysia Taiwan and Turkey. The autocorrelation coefficient is highest in the pre-crises period for 13 of the markets and significant autocorrelation is found in the US market index in the first subperiod. The average return in these emerging markets is positive in the first subperiod and lower in the second subperiod for all of the countries except Poland. The impact of the currency crises is evidenced by the fact that the average daily return in nine emerging markets is negative in the post-crises period. A test of the equality of means across these two subperiods generated a p-value which is less than the significant threshold in eight cases.

[Table 7 here]

Table 8 and 9 present a summary of the performance of the VMA[13] trading rules in forecasting future stock market movements in the pre- and post-currency crises subperiods respectively. Consistent with expectations, the number of buy signals in the pre-crises period is typically greater than the number of sell signals, in the case of Peru by a factor of 4.5 to 1. The two exceptions are China and Korea, where more sell than buy signals are generated. In this period of generally rising markets, the average buy to sell signal ratio across all emerging markets is 2.38. By way of contrast, in the second subperiod, this ratio falls to 1.1 and all countries in the sample generated a near even number of buy and sell trading signals.

[Table 8 here]

[Table 9 here]

Consistent with the full sample results, in the pre-crises period the mean return following a buy signal is positive but only a small number (10%) of the trading rules managed to generate an average return which is significantly greater compared to the average return over the whole sample period. The mean sell return is negative in seven cases and 22 (12.9%) of the trading rules tested produced average returns which were significantly lower than the average return across the subperiod. The spread is significantly different for 61 of the trading rules tested. In the case of the developed

[13] The FMA and TRB strategies as well as bootstrap p-values were also considered and the results do not add to the current discussion.

country benchmark, even though significant autocorrelation is identified in the pre-crises period, none of the spreads are significant.

In the post crises period, the evidence reveals a general decline in the performance of the trading strategies in forecasting future market movements. The mean return following a buy signal remains positive in all cases, however only 10 of the 170 trading rules (7.0%) generated an average returns which are significant. The decline in the performance of the buy signals is more marked as while 14 of the countries exhibited a negative returns on average following a sell signal, only 7 (4.1%) of the rules tested was significant. In terms of the spreads, 48 (28.2%) were significantly different which is below the 35.8% of significant spreads reported in the pre-crises subperiod.

Thus, the previous literature has found that the general nature and direction of movements in the market influence the ability of technical trading strategies to forecast returns. Based on the evidence presented in this paper, the 1997 currency crisis constitutes such an event. Changes in the nature of the market, as evidenced by the significantly lower and even negative average returns, and the observed persistence of trends, as evidenced by the typically lower autocorrelation, appear to have had an impact on the ability of technical trading strategies to forecast future stock price movements. The volatile nature of stock markets around the world post-currency crisis means that markets were lacking the momentum which is essential to the success of these type of trading strategies.

4. Conclusion

This paper considers the ability of a broad range of simple technical trading strategies to forecast future stock market movements for a sample of emerging markets. Unlike the previous literature which has typically only considered one or a few markets, this paper simultaneously tests a broad subset of 17 emerging markets which allows a relative assessment of the usefulness of technical trading to be considered across the emerging markets sector in general. The results of this study lead to a number of interesting conclusions. First, the level of persistence in returns for emerging markets is higher relative to developed markets as proxied in this paper by a US market benchmark. Second, while no technical trading rule proved to be useful when applied to the US data, some trading rules did possess a limited degree of forecasting accuracy. No trading rule systematically generated a significant degree of forecasting accuracy however, and market conditions appear to play a significant role in determining the usefulness of the automated rules. Further to this point, subperiod analysis of technical trading strategies across a pre- and post-1997 currency crises is undertaken. In the pre-crises period, buy signals are generated more often than sell signals at a rate of 2.5:1 on average. In the post-crises period however, the number of trading signals are close to 1:1 and the forecasting accuracy of the trading rules is substantially lower. Finally, the ability of technical trading strategies to forecast future price movements is related to the depth of the market and this information can be to trade profitably in a limited number of cases.

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Table 1
Descriptive Statistics for National Stock Market Index Data

The following table presents summary statistics for daily Datastream national stock market index returns data sampled from the start date listed to September, 2003.

	Sample Start Date	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jaque-Bera Probability	Serial Correlation	No. Obs.
Argentina	Jan. 5, 1988	0.0026	0.3760	-0.6076	0.0341	0.23	39.69	0.000	0.130*	4105
Brazil	July 5, 1994	0.0005	0.1953	-0.1055	0.0177	0.30	14.66	0.000	0.117*	2410
Chile	July 4, 1989	0.0007	0.0668	-0.0494	0.0096	0.19	6.43	0.000	0.304*	3715
China	July 27, 1993	0.0002	0.1071	-0.1429	0.0196	0.07	7.94	0.000	0.178*	2655
Colombia	Jan. 3, 1992	0.0004	0.0989	-0.1020	0.0090	0.21	19.61	0.000	0.318*	3062
India	Jan. 2, 1990	0.0005	0.2572	-0.1825	0.0174	0.31	26.87	0.000	0.098	3585
Indonesia	April 3, 1990	-0.0001	0.1417	-0.1393	0.0174	0.14	11.94	0.000	0.142*	3520
Korea	Sept. 10, 1987	0.0002	0.1134	-0.1269	0.0201	0.13	6.78	0.000	0.041	4188
Malaysia	Jan. 3, 1986	0.0003	0.2039	-0.2222	0.0158	-0.15	35.09	0.000	0.095*	4627
Mexico	Jan. 5, 1988	0.0010	0.1154	-0.1054	0.0160	0.21	10.80	0.000	0.180*	4105
Peru	Jan. 4, 1994	0.0004	0.0996	-0.1022	0.0117	0.53	14.63	0.000	0.151*	2540
Philippines	Sept. 10, 1987	0.0004	0.1481	-0.0856	0.0146	0.68	13.44	0.000	0.182*	4188
Poland	March 2, 1994	-0.0001	0.1627	-0.1043	0.0206	-0.16	8.29	0.000	0.155*	2499
Taiwan	Sept. 10, 1987	0.0002	0.1274	-0.1030	0.0211	0.04	5.18	0.000	0.070*	4188
Thailand	Jan. 5, 1987	0.0003	0.1212	-0.1183	0.0188	0.29	8.58	0.000	0.138*	4366
Turkey	Jan. 5, 1988	0.0019	0.1703	-0.1946	0.0291	-0.02	6.37	0.000	0.091*	4105
Venezuela	Jan. 3, 1990	0.0011	0.2122	-0.1396	0.0233	0.62	12.45	0.000	0.157*	3584
USA	Jan. 3, 1986	0.0003	0.0834	-0.2070	0.0108	-1.71	36.01	0.000	0.030	4627

Table 2

VMA(1,50,0) Trading Rule Estimation Results

The following table presents a summary of the estimation results for a VMA(1,50,0) trading rule applied to daily national stock market data where the first figure in the brackets denotes the short term moving average, the second term denotes the long term moving average and the final term denotes the inclusion of a filter term. The number of buy (sell) signals is the sum of the number of days in which a buy trading signal is generated as a result of the SMA > (<) LMA. The buy (sell) signal average return is the average return to the market following a signal and the t-statistic tests whether it is significantly different from the average return to the market over the sample period. The spread is the difference between the average return to the buy and sell signals and the t-statistics tests whether it is significantly different from zero. The buy (sell) signal σ is a measure of the standard deviation of the returns on buys and sell and proxies the risk attached to the buy and sell signals. The % Buy (Sell) signals > (<) 0 is the fraction of returns to buy (sell) signals which are positive (negative).

	No. of Buy Signals	No. of Sell Signals	Buy Signal Average Return	t-statistic (p-value)	Sell Signal Average Return	t-statistic (p-value)	Buy-Sell Signal Spread	t-statistic (p-value)	Buy Signal σ	Sell Signal σ	% Buy Signals > 0	% Sell Signals < 0
Argentina	2439	1617	0.0047	2.25 (0.004)	-0.0003	-2.95 (0.000)	0.0049	4.50 (0.000)	0.038	0.027	51.05%	53.68%
Brazil	1388	973	0.0010	1.17 (0.148)	-0.0007	-1.48 (0.008)	0.0017	2.29 (0.016)	0.013	0.022	51.30%	48.82%
Chile	2203	1463	0.0016	3.24 (0.000)	-0.0005	-4.25 (0.000)	0.0021	6.48 (0.000)	0.009	0.010	54.33%	50.92%
China	1334	1272	0.0013	1.96 (0.012)	-0.0013	-2.03 (0.000)	0.0027	3.46 (0.000)	0.018	0.021	52.62%	52.83%
Colombia	1564	1449	0.0016	4.56 (0.000)	-0.0010	-4.81 (0.000)	0.0026	8.12 (0.000)	0.009	0.008	54.35%	53.35%
India	1919	1617	0.0020	2.96 (0.000)	-0.0012	-3.31 (0.000)	0.0032	5.43 (0.000)	0.017	0.018	48.62%	47.93%
Indonesia	1742	1729	0.0015	2.93 (0.000)	-0.0015	-2.94 (0.000)	0.0030	5.09 (0.000)	0.016	0.019	50.00%	51.30%
Korea	1954	2185	0.0012	1.87 (0.010)	-0.0008	-1.74 (0.006)	0.0020	3.13 (0.000)	0.019	0.021	48.82%	51.58%
Malaysia	2698	1880	0.0013	2.32 (0.000)	-0.0009	-2.95 (0.000)	0.0022	4.56 (0.000)	0.013	0.019	52.08%	50.85%
Mexico	2540	1516	0.0014	1.45 (0.090)	-0.0001	-2.05 (0.000)	0.0015	3.03 (0.004)	0.014	0.017	52.13%	51.32%
Peru	1425	1066	0.0010	1.94 (0.010)	-0.0007	-2.36 (0.000)	0.0017	3.73 (0.000)	0.010	0.013	51.51%	50.38%
Philippines	2271	1868	0.0018	3.65 (0.000)	-0.0012	-4.15 (0.000)	0.0030	6.75 (0.000)	0.014	0.015	52.05%	52.73%
Poland	1256	1194	0.0013	1.68 (0.004)	-0.0010	-1.74 (0.040)	0.0023	2.97 (0.000)	0.018	0.021	49.44%	47.57%
Taiwan	2107	2032	0.0013	1.97 (0.012)	-0.0009	-2.01 (0.004)	0.0022	3.45 (0.000)	0.019	0.023	48.32%	50.34%
Thailand	2343	1974	0.0017	2.86 (0.000)	-0.0013	-3.21 (0.000)	0.0030	5.26 (0.000)	0.017	0.020	51.52%	51.87%
Turkey	2357	1699	0.0028	1.21 (0.056)	0.0006	-1.50 (0.034)	0.0022	2.35 (0.016)	0.029	0.030	51.63%	50.15%
Venezuela	1904	1631	0.0026	2.28 (0.004)	-0.0006	-2.53 (0.000)	0.0032	4.18 (0.000)	0.024	0.021	49.52%	49.84%
USA	3015	1563	0.0002	-0.15 (0.366)	0.0004	0.24 (0.722)	-0.0001	-0.34 (0.582)	0.008	0.014	50.84%	44.33%

Table 3
VMA Trading Rule Summary by Country

The following table presents a summary of the estimation results for 10 VMA trading rules ((1,50), (1,150), (5,150), (1,200) and (2,200) with an without a threshold term) applied to daily national stock market data. The average number of buy (sell) signals is the average number of trading signals generated across each of the 10 VMA rules considered. The VMA buy (sell) signal return is the average of the buy (sell) signal returns for each of the 10 VMA rules and the number of significant t-statistics is the sum of the number of trading rules which generated a significant result. The buy-sell return spread is the average difference between the return to the buy and sell signals for each of the rules and the number of t-statistics counts the number of rules for which the spread is significant. The buy (sell) signal σ is a measure of the average standard deviation of the returns for each of the trading rules and the % Buy (Sell) signals > (<) 0 is the average fraction of returns to buy (sell) signals which are positive (negative) for the 10 VMA trading rules.

	Average No. of Buy Signals	Average No. of Sell Signals	VMA Buy Signal Return	No. of significant t-statistics (p-values)	VMA Sell Signal Return	No. of significant t-statistics (p-values)	Buy-Sell Return Spread	No. of significant t-statistics (p-values)	Buy Signal σ	Sell Signal σ	% Buy Signals > 0	% Sell Signals < 0
Argentina	2336	1269	0.0042	6 (9)	-0.0001	9 (10)	0.0043	10 (10)	0.0395	0.0241	50.15%	52.83%
Brazil	1315	791	0.0008	0 (0)	0.0001	0 (2)	0.0007	2 (2)	0.0126	0.0227	51.79%	47.00%
Chile	2089	1303	0.0013	3 (10)	-0.0002	9 (10)	0.0014	10 (10)	0.0096	0.0096	53.63%	49.63%
China	1116	1234	0.0007	2 (2)	-0.0007	2 (2)	0.0013	2 (3)	0.0188	0.0210	51.81%	51.64%
Colombia	1518	1288	0.0009	4 (6)	-0.0005	6 (10)	0.0014	10 (10)	0.0092	0.0081	51.79%	51.86%
India	1756	1526	0.0013	2 (6)	-0.0006	5 (8)	0.0020	9 (10)	0.0185	0.0165	47.38%	47.21%
Indonesia	1682	1507	0.0007	2 (3)	-0.0006	2 (3)	0.0013	3 (4)	0.0152	0.0200	48.14%	48.31%
Korea	1760	2023	0.0008	1 (3)	-0.0004	0 (2)	0.0012	2 (3)	0.0187	0.0219	47.85%	50.20%
Malaysia	2691	1578	0.0009	2 (7)	-0.0006	6 (10)	0.0015	10 (10)	0.0122	0.0211	51.85%	50.28%
Mexico	2612	1132	0.0011	0 (1)	0.0005	1 (2)	0.0006	2 (2)	0.0138	0.0172	51.18%	50.14%
Peru	1428	854	0.0007	1 (2)	-0.0003	2 (7)	0.0010	2 (8)	0.0101	0.0132	50.11%	49.36%
Philippines	2223	1647	0.0012	4 (9)	-0.0006	6 (10)	0.0018	10 (10)	0.0133	0.0157	50.67%	50.41%
Poland	1221	988	0.0007	1 (2)	-0.0001	0 (1)	0.0007	2 (2)	0.0172	0.0201	48.79%	47.70%
Taiwan	1950	1889	0.0010	2 (7)	-0.0007	1 (10)	0.0018	10 (10)	0.0189	0.0228	48.81%	50.24%
Thailand	2278	1698	0.0007	2 (2)	-0.0003	2 (2)	0.0010	2 (2)	0.0173	0.0215	49.60%	50.67%
Turkey	2506	1236	0.0027	0 (2)	0.0008	0 (3)	0.0020	4 (7)	0.0287	0.0317	51.31%	49.93%
Venezuela	1883	1325	0.0017	2 (2)	-0.0001	2 (8)	0.0019	5 (8)	0.0227	0.0237	48.18%	49.61%
USA	3031	1197	0.0004	0 (0)	0.0002	0 (0)	0.0002	0 (0)	0.0085	0.0157	51.45%	45.97%

Table 4
FMA Trading Rule Summary by Country

The following table presents a summary of the estimation results for 10 FMA trading rules ((1,50), (1,150), (5,150), (1,200) and (2,200) with an without a threshold term) applied to daily national stock market data. The average number of buy (sell) signals is the average number of trading signals generated across each of the 10 FMA rules considered. The FMA buy (sell) signal return is the average of the buy (sell) signal returns for each of the 10 FMA rules and the number of significant t-statistics is the sum of the number of trading rules which generated a significant result. The buy-sell return spread is the average difference between the return to the buy and sell signals for each of the rules and the number of t-statistics counts the number of rules for which the spread is significant. The buy (sell) signal σ is a measure of the average standard deviation of the returns for each of the trading rules and the % Buy (Sell) signals > (<) 0 is the average fraction of returns to buy (sell) signals which are positive (negative) for the 10 FMA trading rules.

	Average No. of Buy Signals	Average No. of Sell Signals	VMA Buy Signal Return	No. of significant t-statistics (p-values)	VMA Sell Signal Return	No. of significant t-statistics (p-values)	Buy-Sell Return Spread	No. of significant t-statistics (p-values)	Buy Signal σ	Sell Signal σ	% Buy Signals > 0	% Sell Signals < 0
Argentina	244	133	0.0377	0 (6)	0.0019	5 (10)	0.0358	10 (6)	0.146	0.086	56.01%	49.70%
Brazil	136	79	0.0060	0 (0)	0.0012	0 (0)	0.0048	0 (0)	0.051	0.069	59.07%	44.12%
Chile	215	135	0.0112	1 (10)	0.0000	4 (10)	0.0113	10 (6)	0.042	0.040	58.95%	53.23%
China	116	124	0.0055	0 (1)	-0.0067	1 (5)	0.0122	2 (4)	0.068	0.076	52.06%	55.60%
Colombia	155	131	0.0070	2 (2)	-0.0025	2 (10)	0.0095	2 (6)	0.041	0.041	58.53%	56.10%
India	180	157	0.0118	2 (6)	-0.0044	2 (8)	0.0162	6 (6)	0.068	0.061	55.22%	52.66%
Indonesia	172	148	0.0052	2 (2)	-0.0042	2 (2)	0.0094	2 (3)	0.053	0.070	55.60%	52.93%
Korea	180	212	0.0081	1 (4)	-0.0036	0 (1)	0.0117	3 (5)	0.060	0.064	52.13%	55.42%
Malaysia	275	162	0.0083	2 (3)	-0.0045	2 (7)	0.0128	6 (6)	0.049	0.062	60.72%	52.27%
Mexico	270	117	0.0105	0 (0)	0.0056	0 (1)	0.0049	0 (0)	0.049	0.058	60.30%	43.87%
Peru	147	87	0.0062	0 (0)	-0.0029	0 (8)	0.0091	1 (4)	0.035	0.048	58.26%	53.57%
Philippines	226	170	0.0099	1 (6)	-0.0035	4 (8)	0.0135	6 (6)	0.050	0.061	58.23%	53.62%
Poland	127	91	0.0040	0 (0)	0.0014	0 (0)	0.0026	0 (0)	0.057	0.066	50.96%	53.60%
Taiwan	198	197	0.0095	2 (6)	-0.0063	1 (7)	0.0158	6 (6)	0.071	0.068	56.54%	51.71%
Thailand	234	177	0.0048	2 (2)	-0.0007	2 (2)	0.0055	2 (2)	0.063	0.076	56.13%	50.56%
Turkey	255	121	0.0240	0 (1)	0.0139	0 (0)	0.0100	0 (1)	0.106	0.106	57.37%	47.01%
Venezuela	194	139	0.0161	1 (2)	-0.0001	0 (6)	0.0161	2 (5)	0.089	0.085	52.67%	50.65%
USA	505	262	0.0034	0 (0)	0.0019	0 (0)	0.0015	0 (0)	0.029	0.038	56.79%	46.08%

Table 5
TRB Trading Rule Summary by Country

The following table presents a summary of the estimation results for 6 TRB trading rules ((1,50), (1,150) and (1,200) with an without a threshold term) applied to daily national stock market data. The average number of buy (sell) signals is the average number of trading signals generated across each of the 6 TRB rules considered. The TRB buy (sell) signal return is the average of the buy (sell) signal returns for each of the 6 TRB rules and the number of significant t-statistics is the sum of the number of trading rules which generated a significant result. The buy-sell return spread is the average difference between the return to the buy and sell signals for each of the rules and the number of t-statistics counts the number of rules for which the spread is significant. The buy (sell) signal σ is a measure of the average standard deviation of the returns for each of the trading rules and the % Buy (Sell) signals > (<) 0 is the average fraction of returns to buy (sell) signals which are positive (negative) for the 6 TRB trading rules.

	Average No. of Buy Signals	Average No. of Sell Signals	VMA Buy Signal Return	No. of significant t-statistics (p-values)	VMA Sell Signal Return	No. of significant t-statistics (p-values)	Buy-Sell Return Spread	No. of significant t-statistics (p-values)	Buy Signal σ	Sell Signal σ	% Buy Signals > 0	% Sell Signals < 0
Argentina	382	147	0.0113	6 (6)	-0.0041	4 (3)	0.0154	6 (6)	0.0504	0.0341	57.26%	53.85%
Brazil	192	75	0.0035	6 (6)	-0.0047	0 (5)	0.0082	2 (6)	0.0116	0.0458	61.61%	57.01%
Chile	402	152	0.0051	6 (6)	-0.0031	6 (6)	0.0082	6 (6)	0.0104	0.0121	68.31%	57.18%
China	162	129	0.0071	6 (6)	-0.0058	2 (6)	0.0129	6 (6)	0.0214	0.0304	63.16%	60.85%
Colombia	301	182	0.0051	6 (6)	-0.0044	6 (6)	0.0096	6 (6)	0.0091	0.0085	70.19%	65.78%
India	289	154	0.0040	6 (6)	-0.0037	4 (6)	0.0077	6 (6)	0.0162	0.0210	56.71%	58.17%
Indonesia	220	197	0.0043	6 (6)	-0.0044	4 (6)	0.0087	6 (6)	0.0151	0.0253	58.53%	57.33%
Korea	237	216	0.0018	2 (2)	0.0018	0 (0)	-0.0001	0 (0)	0.0208	0.0268	53.71%	52.86%
Malaysia	463	148	0.0035	6 (6)	-0.0040	2 (6)	0.0075	4 (6)	0.0119	0.0316	61.03%	52.50%
Mexico	476	101	0.0034	6 (6)	-0.0020	0 (2)	0.0054	2 (6)	0.0118	0.0254	58.70%	57.75%
Peru	201	115	0.0031	6 (6)	-0.0026	4 (6)	0.0057	6 (6)	0.0101	0.0145	57.86%	56.38%
Philippines	319	203	0.0059	6 (6)	-0.0055	6 (6)	0.0114	6 (6)	0.0168	0.0216	63.74%	59.37%
Poland	153	106	0.0021	0 (2)	-0.0019	2 (2)	0.0040	2 (2)	0.0193	0.0237	55.35%	53.03%
Taiwan	292	206	0.0035	6 (6)	-0.0022	0 (2)	0.0057	6 (6)	0.0185	0.0274	54.68%	49.21%
Thailand	327	190	0.0036	6 (6)	-0.0048	6 (6)	0.0085	6 (6)	0.0169	0.0249	56.36%	56.84%
Turkey	428	102	0.0104	6 (6)	0.0010	0 (0)	0.0094	2 (6)	0.0286	0.0445	65.25%	56.53%
Venezuela	273	153	0.0113	6 (6)	-0.0038	4 (4)	0.0151	6 (6)	0.0287	0.0247	64.58%	51.99%
USA	514	95	0.0007	0 (0)	0.0023	0 (0)	-0.0016	0 (0)	0.0063	0.0226	52.66%	39.09%

Table 6
Pre-Cost Trading Returns to Technical Trading Strategies

The following table presents a summary of the buy-hold return to each national stock market index as well as the sum of the product of the number of signals and the average return to both the buy and sell signals for the VMA(1,50,0) rule. Estimates of the trading costs for the sample markets are presented in the final three columns.

	Panel A			Panel B	Panel C			
	Buy-Hold Return	VMA(1,50,0) Return	Difference	2002 Turnover Ratio[a] (%)	One-Way Trading Costs[b] (Basis Points)	One-Way Trading Costs[c] (Basis Points)	One-Way Trading Costs[d] (%)	Round Trip Trading Costs[e] (%)
Argentina	1074.65%	1194.84%	120.19%	1.5	47.3	34.59	0.32	na
Brazil	119.66%	206.91%	87.25%	32.0	36.7	30.36	0.26	2.4274
Chile	265.04%	425.63%	160.59%	6.0	45.7	65.20	0.69	na
China	39.82%	338.78%	298.96%	67.6	na	na	0.13	1.0508
Colombia	120.99%	395.14%	274.15%	2.4	55.3	54.84	na	na
India	177.81%	577.84%	400.03%	165.0	14.0	38.48	0.48	0.3931
Indonesia	-12.70%	520.65%	533.35%	47.6	85.2	57.67	0.46	3.4565
Korea	66.33%	409.28%	342.95%	321.5	63.1	43.60	0.34	1.0769
Malaysia	158.02%	519.94%	361.92%	22.7	73.8	42.95	na	na
Mexico	416.23%	370.76%	-45.47%	23.9	34.4	28.86	0.24	na
Peru	95.86%	217.12%	121.26%	9.3	60.6	35.34	na	4.9739
Philippines	162.49%	632.94%	470.45%	7.6	103.2	78.58	0.52	na
Poland	-15.09%	282.68%	297.77%	22.4	na	na	na	1.0792
Taiwan	78.05%	456.79%	378.74%	226.3	56.0	39.64	0.29	na
Thailand	150.08%	654.93%	504.85%	114.0	69.6	50.51	na	2.0819
Turkey	766.49%	558.02%	-208.47%	170.1	41.0	33.85	0.12	na
Venezuela	400.93%	592.90%	191.97%	2.5	99.4	41.63	0.80	na
USA	165.55%	-2.22%	-167.77%	204.1	8.3	17.44	na	1.5245

Note - na denotes data 'not available'.
- 'a' Turnover ratio data sourced from the Standard and Poors Global Stock Markets Factbook (2003).
- 'b' data reproduced from Domowitz, Glen and Mahavan (2001). Average trading costs over the period 1996 – 1998.
- 'c' Elkins/McSherry data for 2002 trading costs sourced from the Standard and Poors Global Stock Markets Factbook (2003).
- 'd" data reproduced from Chakravarty, Chiyachantana and Jiang (2004).
- 'e' data reproduced from Swan and Westerholm (2005). USA data is the average of NYSE and NASDAQ and China is the average of the Shanghai and Shenzhen exchanges.

Table 7
Summary of National Stock Market Return Data: Pre- and Post-Currency Crises

The following table presents a summary of the national stock markets return data pre- and post-July 2, 1997 which is chosen as the date on which the Asian currency crises commenced. The buy and hold return is the log change in the national stock market index from the beginning of the sample period to the date of the crises and from the crises date to the end of the sample period.

	Pre-Crises Buy and Hold Return	Post-Crises Buy and Hold Return	Serial Correlation Pre-Crises	Serial Correlation Post-Crises	Mean Return Pre-Crises	Mean Return Post-Crises	Mean Return Equality#
Argentina	1064.4%	9.9%	0.1243 *	0.1466 *	0.0042	0.0001	0.000
Brazil	90.7%	26.8%	0.1356 *	0.1065 *	0.0011	0.0002	0.017
Chile	249.5%	14.5%	0.2988 *	0.3068 *	0.0012	0.0001	0.000
China	45.7%	-4.8%	0.2701 *	0.1502 *	0.0004	-0.0001	0.428
Colombia	127.5%	-6.7%	0.3266 *	0.3047 *	0.0008	-0.0001	0.000
India	149.1%	28.2%	0.1084 *	0.0811 *	0.0007	0.0002	0.125
Indonesia	29.6%	-42.2%	0.2443 *	0.1143 *	0.0001	-0.0003	0.413
Korea	34.9%	28.4%	0.0174	0.0520 *	0.0001	0.0002	0.908
Malaysia	190.8%	-33.4%	0.1665 *	0.0334	0.0006	-0.0002	0.083
Mexico	379.6%	35.5%	0.2034 *	0.1277 *	0.0015	0.0002	0.000
Peru	102.9%	-7.4%	0.1552 *	0.1410 *	0.0011	-0.0001	0.000
Philippines	229.0%	-65.1%	0.1881 *	0.1719 *	0.0008	-0.0004	0.000
Poland	-29.9%	15.6%	0.2056 *	0.1015 *	-0.0003	0.0001	0.307
Taiwan	119.0%	-40.1%	0.0892 *	0.0268	0.0004	-0.0002	0.131
Thailand	154.7%	-13.4%	0.1602 *	0.1168 *	0.0005	-0.0001	0.219
Turkey	563.2%	202.9%	0.1945 *	-0.0042	0.0022	0.0012	0.215
Venezuela	417.4%	-17.6%	0.1470 *	0.1693 *	0.0021	-0.0001	0.000
USA	203.7%	13.2%	0.1149 *	-0.0020	0.0003	0.0001	0.467

Note : # denotes p-values reported for a test of the equality of mean returns in the pre and post crises subperiods

Table 8
Pre-Currency Crisis VMA Trading Rule Analysis

The following table presents a summary of the results for the VMA trading rules applied to data sampled in the pre-currency crises period.

	Average No. of Buy Signals	Average No. of Sell Signals	VMA Buy Signal Return	No. of significant t-statistics	VMA Sell Signal Return	No. of significant t-statistics	Buy-Sell Return Spread	No. of significant t-statistics
Argentina	1600	559	0.0057	1	0.0005	4	0.0052	10
Brazil	477	123	0.0011	0	0.0022	0	-0.0011	0
Chile	1349	509	0.0016	2	0.0003	2	0.0013	5
China	347	450	0.0003	0	-0.0003	0	0.0006	2
Colombia	634	606	0.0013	2	-0.0001	2	0.0014	6
India	961	768	0.0018	2	-0.0008	3	0.0025	7
Indonesia	999	625	0.0008	2	-0.0002	2	0.0010	2
Korea	1028	1198	0.0006	1	-0.0003	0	0.0009	2
Malaysia	1987	722	0.0009	0	0.0001	2	0.0009	4
Mexico	1809	423	0.0014	0	0.0013	0	0.0001	2
Peru	607	134	0.0009	0	0.0024	0	-0.0015	0
Philippines	1672	641	0.0015	2	-0.0002	3	0.0016	5
Poland	461	223	0.0012	0	0.0002	0	0.0011	1
Taiwan	1294	1002	0.0013	1	-0.0007	0	0.0020	4
Thailand	1547	884	0.0008	2	0.0000	2	0.0008	2
Turkey	1591	620	0.0032	1	0.0010	1	0.0023	3
Venezuela	1135	606	0.0029	1	0.0000	1	0.0028	6
USA	2155	518	0.0005	0	0.0005	0	0.0000	0

Table 9
Post-Currency Crisis VMA Trading Rule Analysis

The following table presents a summary of the results for the VMA trading rules applied to data sampled in the post-currency crises period.

	Average No. of Buy Signals	Average No. of Sell Signals	VMA Buy Signal Return	No. of significant t-statistics	VMA Sell Signal Return	No. of significant t-statistics	Buy-Sell Return Spread	No. of significant t-statistics
Argentina	657	658	0.0009	0	-0.0008	1	0.0017	2
Brazil	769	590	0.0008	0	-0.0002	0	0.0010	2
Chile	678	708	0.0009	2	-0.0003	2	0.0012	7
China	712	695	0.0009	1	-0.0005	0	0.0014	2
Colombia	768	649	0.0006	2	-0.0008	2	0.0014	9
India	719	691	0.0010	1	-0.0004	0	0.0014	2
Indonesia	641	779	0.0006	1	-0.0009	0	0.0015	2
Korea	685	734	0.0015	0	-0.0005	0	0.0020	2
Malaysia	705	706	0.0009	1	-0.0007	0	0.0017	3
Mexico	685	687	0.0005	0	0.0000	0	0.0005	0
Peru	776	622	0.0007	1	-0.0007	1	0.0013	10
Philippines	540	869	0.0004	2	-0.0007	0	0.0011	2
Poland	696	685	0.0003	0	-0.0003	0	0.0006	2
Taiwan	585	818	0.0006	0	-0.0009	0	0.0015	1
Thailand	703	696	0.0005	1	-0.0006	1	0.0011	2
Turkey	767	616	0.0014	0	0.0006	0	0.0008	0
Venezuela	661	660	0.0002	0	0.0000	0	0.0002	0
USA	729	678	0.0001	0	0.0000	0	0.0001	0