Technical Analysis Around the World: Does it Ever Add Value?

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Abstract

Technical analysis is not consistently profitable in the 49 countries that comprise the Morgan Stanley Capital Index once data snooping bias is accounted for. There is some evidence that technical trading rules perform better in emerging markets than developed markets, which is consistent with the finding of previous studies that these markets are less efficient, but this result is not strong. While we cannot rule out the possibility that technical analysis compliments other market timing techniques or that trading rules we do not test are profitable, we do show that over 5,000 trading rules do not add value beyond what may be expected by chance when used in isolation.

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Abstract

Technical analysis is not consistently profitable in the 49 countries that comprise the Morgan Stanley Capital Index once data snooping bias is accounted for. There is some evidence that technical trading rules perform better in emerging markets than developed markets, which is consistent with the finding of previous studies that these markets are less efficient, but this result is not strong. While we cannot rule out the possibility that technical analysis compliments other market timing techniques or that trading rules we do not test are profitable, we do show that over 5,000 trading rules do not add value beyond what may be expected by chance when used in isolation.

1. Introduction

Technical analysis, which involves making investment decisions based on past price movements, continues to prove very popular with the investment community.[1] Technical trading rules are closely related to momentum trading strategies, which involve buying (selling) winner (loser) stocks. Most academic authors find that momentum is an enduring anomaly which has led to Fama and French (2008, p. 1) describing it as "pervasive." These two factors have resulted in a large amount of research energy being devoted to investigating whether technical trading rules can add value. Most studies find that technical analysis does not add value in the US equity market, but several authors have presented supportive evidence in emerging markets.

We add to the literature by investigating the profitability of technical trading rules in the 49 developed and emerging markets that make up the Morgan Stanley Capital Index (MSCI). In doing so we propose that we make several important contributions. Firstly, we consider in excess of 5,000 trading rules from four different rule families on each market. Most previous studies consider a smaller number of rules (often less than 20).

Secondly, we apply a robust methodology which involves the application of two alternative bootstrap techniques. The first was introduced by Brock, Lakonishok, and LeBaron (1992) and the second was introduced by Sullivan, Timmermann, and White (1999). These techniques have been shown to be more appropriate than the traditional t-test approach which many authors in this area rely on. The Sullivan et al. (1999) technique is particularly important as it enables us to control for data snooping bias, which they show can be the main determinant of apparent technical analysis profits.

[1] See Taylor and Allen (1992), Lui and Mole (1988), and Cheung and Chinn (2001) for surveys of investment professionals which illustrate the importance they ascribe to technical analysis.

Thirdly, our investigation of the same rules over a large number of markets enables important comparisons to be made between developed and emerging markets. Chaudhuri and Wu (2003) find that the random walk hypothesis can be rejected in many emerging markets which implies that technical trading rules may be more profitable in these markets than they are in developed markets. We are unaware of any previous studies that compare profits to the same rules in both developed and emerging markets using data snooping adjusted bootstrap techniques.

Finally, the careful design of our experiment ensures our results are likely to be of interest to the investment community. The importance of international markets to portfolio managers continues to increase with a recent survey finding the average allocation of money to international markets by global funds was 57 percent in 2006 compared with just 37 percent in 2002.[2] We purposely use MSCI indices as these are the benchmark adopted by asset managers around the world. Portfolio managers could apply technical trading strategies to time their entry into stocks within markets as part of a top-down investment approach as outlined by Chan, Hameed, and Tong (2000), or they could use the trading rules we document to time their purchase of the many ETFs and derivative products which are based on MSCI indices. Olson (2004) shows that the profits to technical analysis have declined over time so our focus on the recent period of 2001 – 2007, for which MSCI daily data are available, is important. Finding profits on historical data may not necessarily imply that profits are available today.

We find that many technical trading rules produce statistically significant profits before consideration is given to data snooping bias, but this profitability disappears after data snooping bias is taken into account. There is some evidence that technical analysis is more profitable in emerging markets than it is in developed markets but this trend is relatively

[2] http://www.iht.com/articles/2007/04/25/bloomberg/bxfund.php.

weak. We conclude that the technical trading rules we consider do not add value beyond what might be expected by chance as a stand-alone market timing tool, but we cannot rule out the possibility that these technical trading rules can compliment some other investment technique, or that other trading rules are profitable.[3] Our intention was to also assess the economic significance of the most profitable trading rules, but given that the profitability of even the best performing rule on each market does not fall outside that which can be explained by data snooping we do not proceed with this step.

The rest of this paper is organized as follows: Section 2 contains a brief review of the literature. Our data and methodology are outlined in Section 3. We present our results in Section 4 and discuss our conclusions in Section 5.

2. Literature Review

The majority of US studies find that technical analysis does not add value after transaction costs are accounted for. In a seminal paper, Brock, Lakonishok and LeBaron (hereafter BLL) (1992) test Variable Moving Average (VMA), Fixed Moving Average (FMA) and Trading Rang Breakout (TRB) rules on the Dow Jones Industrial Average and find that statistically significant profits are generated. However, Bessembinder and Chan (1998) show that these profits do not exceed reasonable estimates of transaction costs. Allen and Karjalainen (1999) reach a similar conclusion after applying trading rules selected by genetic algorithms to the US equity market. While there are gross profits available, the profitability is removed once transaction costs are accounted for. Exceptions to the above are the minority but they do exist. For instance Cooper (1999) finds filter rules based on both

[3] There are a huge number of different trading rules used by practitioners and many systems include customized parameter specifications and combinations of different rules but we limit our analysis to those most commonly studied in the literature, as summarized by Sullivan et al (1999). We provide detailed explanations of these rules in Section 3.

price and volume generate profits after relatively low estimates of transaction costs are taken into account.

Authors who have tested trading rules on developed markets outside the US generally also find that the profits generated do not offset transactions costs. Hudson, Dempsey, and Keasey (1996) apply the BLL (1992) trading rules in the UK equity market and find that they generate profitable signals but these profits are not large enough to offset transaction costs. Precise estimation of the costs incurred in exploiting technical analysis are often difficult to estimate but Bessembinder and Chan (1995) find BLL (1992) trading rules are less profitable in the developed markets of Hong Kong and Japan than they are in emerging markets.

The evidence of profitability over and above transactions costs appears to be the most compelling in emerging markets. Parisi and Vasquez (2000) document large profits to the BLL (1992) trading rules in the Chilean stock market. They do not consider transactions costs, however, several other authors do. Bessembinder and Chan (1995) find BLL (1992) trading rules produce profits in excess of transaction costs in the emerging markets of Malaysia, Thailand, and Taiwan. Ito (1999) also tests BLL (1992) trading rules and finds profitability beyond transaction costs in Indonesian, Mexican and Taiwanese equity indices. Finally, Ratner and Leal (1999) test 10 VMA rules on the emerging markets of India, Korea, Malaysia, Philippines, Taiwan, Thailand, Argentina, Brazil, Chile, and Mexico. They find some evidence of profitability in most markets after transactions costs but most of this is centred in the markets of Mexico, Philippines, Taiwan, and Thailand.

It is important to note that none of the studies discussed above formally address the issue of data snooping bias with the technique outlined by Sullivan, Timmermann, and White (1999). Drawing on the work of White (2000), these authors suggest that rules that are the most profitable are the very rules that are the most likely to be examined over time. This means that it is important to consider the profitability of any rule in the context of the full universe of rules from which it was drawn. We apply the technique advocated by Sullivan, Timmermann, and White (1999) to our test of technical analysis profitability in both developed and emerging markets.

3. Data, Trading Rule Specifications, and Methodology

3.1. Data

We source data for the 23 developed markets and 26 emerging markets that comprise the MSCI from Datastream. We report results for their total return series in US$ but we test local currency series for a number of countries and verify there results are qualitatively identical. We source data for the 1/1/2001 – 31/12/2007 period for each country with the exception of Greece whose data begins at 1/6/2001. These periods correspond to the first date that daily data is available for the MSCI for each country. We suggest that the focus on data for a recent time period is appropriate as Olson (2004) has shown that the returns to technical analysis have declined over time, which means that documenting profits on more historical series may not be relevant.

The summary statistics presented in Table 1 illustrate that emerging markets have, on average, out-performed their developed market counterparts over the period of our study (mean daily return of 0.11% for emerging markets versus 0.05% for developed markets), but they also involve higher risks. The average standard deviation across the emerging markets is 1.70% versus an average of 1.27% for developed markets. All the markets we study have gained over the 2001-2007 period. Columbia is the best performing while the USA is the worst performing. Turkey is the most risky market, based on standard deviations, while Malaysia is the least risky. Many markets display skewness and kurtosis which reinforces the appropriateness of our non-parametric bootstrap methodologies, which we discuss in detail in Section 3.3.

[Insert Table 1 About Here]

3.2. Trading Rule Specifications

We apply 5,806 of the technical trading rules suggested by Sullivan, Timmermann, and White (here after STW) (1999). STW (1999) test in excess of 7,000 rules, but one of their five rule families requires volume data which are not available for the MSCI indices we examine. The four rule families we test are Filter Rules, Moving Average Rules, Support and Resistance Rules, and Channel Break-outs. STW (1999) provide an excellent description of each rule in the appendix of their paper, which we recommend to the interested reader.

Basic Filter Rules involve opening long (short) positions after price increases (decreases) by x% and closing these postions when price decreases (increases) by x% from a subsequent high (low). We test these rules and two variations. Following STW (1999) we also investigate defining subsequent high (lows) as the highest (lowest) closing price achieved while holding a particular long (short) position, and a most recent closing price that is less (greater) than the e previous closing prices. We also apply rules that permit a neutral position. These involve closing a long (short) position when price decreases (increases) y percent from the previous high (low). Finally, we also consider rules that involve holding a position for a pre-specified number of periods, c, thereby ignoring other signals generated during this time.

Moving Average rules generate buy (sell) signals when the price or a short moving average moves above (below) a long moving average. We follow STW (1999) and apply two filters. The first variation involves the requirement that the shorter moving average exceeds the longer moving average by a fixed amount, *b*. The second variation involves the requirement that a signal, either buy or sell, remains valid for a prespecified number of periods, *d*, before the signal is acted upon. A final variation we consider is holding a position for a prespecified number of periods, *c*.

Our third rule family, Support and Resistance or "Trading Range Break" rules involve opening a long (short) position when the closing price breaches the maximum (minimum) price over the previous *n* periods. A variation we consider involves using the most recent closing price that is greater (less) than the *e* previous closing price as the extreme price level that triggers an entry or exit signal. Consistent with the other rule families, positions can be held for fixed number of periods, *c*. Finally, we follow STW (1999) and impose a fixed percentage band filter, *b*, and a time delay filter, *d*.

Our final family of rules is Channel Breakouts. In accordance with STW (1999), the Channel Breakout rules we test involve opening long (short) positions when the closing price moves above (below) the channel. A channel is defined as a situation when the high over the previous *n* periods is within *x* percent of the low over the previous *n* periods. Positions are held for a fixed number of periods, *c*. A version of Channel Breakout rules which involve a fixed band, *b*, being applied to the channel as a filter is also investigated.

3.3. Methodology

We follow the approach of Marshall, Cahan, and Cahan (2008a, b) and apply both the BLL (1992) and STW (1999) bootstrap methodologies. The BLL (1992) methodology involves fitting a null model to the data and estimating its parameters. The residuals are then randomly re-sampled 500 times and used, together with the models parameters, to generate random price series which exhibit the same characteristics as the original series. BLL (1992) find that results do not differ in any important way regardless of which null model is used, however, we follow (Kwon and Kish (2002) and Marshall, Cahan, and Cahan (2008b) and use the GARCH-M null model which we present in equations 1 to 3 (see BLL, 1992 for a detailed description of this model):

$$r_t = \alpha + \gamma\sigma_t^2 + \beta\varepsilon_{t-1} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

$$\varepsilon_t = \sigma_t z_t \qquad\qquad z_t \sim N(0,1) \tag{3}$$

The basic premise behind the BLL (1992) bootstrap methodology is that in order for a trading rule to be statistically significant at the α level it must produce larger profits on less than α% of the bootstrapped series than on the original series. In accordance with BLL (1992) we define the buy (sell) return as the mean return for each day the rule is long (short). The difference between the two means is the buy-sell return and the proportion of times the buy-sell profit for the rule is greater on the 500 random series than the original series is the buy-sell p-value.

The second bootstrap test we apply is from STW (1999). Their test is based on the techniques introduced by White (2000), which are based on the premise that the statistical significance of any profits to a technical trading rule need to be adjusted to account for the fact that the trading rule in question was drawn from a universe of trading rules. This means that it is possible that its profitability is simply due to chance. In this sense the STW (1999) approach is different from the BLL (1992) technique which evaluates each rule in isolation.

In accordance with STW (1999), we define $f_{k,t}$ $(k = 1,...,M)$ as the period t return generated by the k-th trading rule relative to the benchmark index return at time t). The main statistic we are interested in is the mean period relative return from the k-th rule, $\bar{f}_k = \sum_{t=1}^{T} f_{k,t} / T$, where T is the number of days in the sample.

Consistent with STW (1999), we use the null hypothesis that the performance of the best trading rule on each index is no better than the benchmark performance, i.e.,

$$H_0 : \max_{k=1,...,M} \bar{f}_k \leq 0 \tag{4}$$

Following STW (1999) we use a stationary bootstrap of on the M values of $\bar{f}_k$ to test the null hypothesis.[4] This involves re-sampling with replacement the time-series of relative returns B times for each of the M rules. For each of the M rules, the same B bootstrapped time-series are used. In accordance with STW (1999), we set $B = 500$. For the k-th rule, this results in B means being generated, which we denote $\bar{f}^*_{k,b}$ $(b = 1,...,B)$, from the B re-sampled time-series, where:

$$\bar{f}^*_{k,b} = \sum_{t=1}^{T} f^*_{k,t,b} / T \ , \quad (b = 1,...,B) . \tag{5}$$

The test two statistics employed in the test are:

$$\bar{V}_M = \max_{k=1,...,M} [\sqrt{T}\, \bar{f}_k] \tag{6}$$

and

$$\bar{V}^*_{M,b} = \max_{k=1,...,M} [\sqrt{T} (\bar{f}^*_{k,b} - \bar{f}_k)] \quad , \quad (b = 1,...,B). \tag{7}$$

[4] The interested reader should consult Appendix C of STW (1999) for more details.

The test statistic is derived by comparing $\overline{V}_M$ to the quantiles of the $\overline{V}^*_{M,b}$ distribution. In other words, we compare the maximum mean relative return from the original series, to that from each of the 500 bootstraps. Or, put another way, the test evaluates the performance of the best rule with reference to the performance of the whole universe and takes account of data snooping bias in the process.

4. Results

Our results indicate that there is no evidence that the technical trading rules we consider consistently add value after data snooping bias is taken into account. There is widespread evidence of rules producing statistically significant profits, but the statistical significance is not strong enough to rule out the possibility that it could be due to chance. We find some evidence that technical analysis is more profitable in emerging markets but this is relatively weak. We intended to also determine the economic significance of the most profitable trading rules, but given that the profitability of even the best performing rule on each market is not sufficient to rule out a data snooping explanation we see little point proceeding with this analysis.

The first part of the results we present are generated using the bootstrapping technique of BLL (1992). This involves fitting a null model to the data, in our case GARCH-M, and bootstrapping the residuals to generate random series with the same time-series characteristics as the original series. A trading rule is then run over the random series and the profits compared to those generated on the original series. For a rule to be statistically significant at the 5% level the profits must be larger on the random bootstrapped series than the original series less than 5% of the time. The BLL (1992) approach takes no account of data snooping bias. In Table 2 we present the number of rules, out of the total universe of 5,806, which are profitable at the 1%, 5%, and 10% levels respectively. Results for developed (emerging) markets are presented in Panel A (Panel B).

The Table 2 results indicate that technical analysis appears to be more profitable on emerging markets than developed markets. Across all emerging markets the average number of rules that are statistically significant at the 1%, 5%, and 10% level is 90, 395, and 791 respectively. This equivalent average numbers of profitable rules for developed markets are 41, 220, and 492. Comparing the developed and emerging markets another way, we see that 15 out of the 26 developed markets have more than 10% of the total number of rules (i.e. more than 580) statistically significant at the 10% level compared to 7 of the 23 developed markets.

Turning to the individual results, it is clear that there is a lot of variation in the number of rules that are statistically significant in the developed and emerging market sub-samples. Of the developed markets, Japan has the fewest statistically significant rules (186 at the 10% level), while Portugal has the most (1258 at the 10% level). Within the emerging markets, Korea has the fewest number of statistically significant rules at the 10% level (162) while Indonesia has the most (1254).

[Insert Table 2 About Here]

We now consider the results generated by the STW (1999) bootstrap techniques. Unlike, the BLL (1992) results, data-snooping bias is accounted for in these results. We present the nominal p-value which is generated by the best performing rule before data snooping bias is accounted for. It is important to note that the bootstrapping technique used by STW (1999) to generate the nominal p-value is different to the BLL (1992) procedure. The

STW p-value includes the adjustment for data snooping bias. We also present the following statistics for the best performing rule: the average daily return, the average return per trade, the total number of trades, the number of winning trades, the number of losing trades, and the average number of days per trade.

The developed market results in Panel A of Table 3 indicate that the best trading rule produces profits that are statistically significant at the 10% level or better, based on the STW (1999) bootstrap procedure, in 16 of the 23 developed markets prior to any adjustment for data snooping bias. As noted earlier, this bootstrap procedure is different to that developed by BLL (1992). This accounts for the fact that some markets have no rules that generate profits that are statistically significant in these results whereas each market has rules that generate statistically significant profits based on the BLL (1992) technique. While there may be some differences between the results generated by the BLL (1992) and STW (1999) techniques prior to data snooping bias adjustment, the result after this adjustment has been made is unambiguously clear. None of the developed markets have a trading rule that produces statistically significant profits after data snooping bias is accounted for. Data snooping is clearly a major issue, judging by the differences between the nominal and STW p-values. For instance in the case of Singapore the nominal p-value is 0.05, yet when data snooping bias is taken into account the p-value increases to 0.802.

It is clear that there is a large amount of variation in the trading frequency of the best performing trading rule across the different markets. In markets such as Australia and Austria the most profitable rule is from the Support and Resistance rule family. In both cases the rule only signals a total of 4 trades in the entire seven year period. The average number of days a trade is open is 431 in the case of Australia. This explains why the average return per trade is very sizable (38.16%) yet the average daily return is just 0.08%, and therefore almost identical to the unconditional average daily return (0.08%) in the Australian market during the period we study.

At the other end of the spectrum, the best performing rule in other markets signals many trades. In Sweden the optimal rule is a short term moving average rule which generates a total of 861 trading signals resulting in an average holding period of just 2 days. The results for this rule illustrate that a technical trading rule can be profitable overall even if it generates more losing than winning trades. The best performing rule in Sweden only signals a winning trade 40% of the time but it is still profitable overall due to the fact that the average profits generated by its winning trades outweigh the average profits generated by its losing trades.

[Insert Table 3 About Here]

The emerging market results in Panel B of Table 3 are similar to their developed market counterparts in that no market has a trading rule that generates profits that are statistically significant at the 10% level after data snooping bias is taken into account. The closest any market gets is Colombia, whose best performing rule only just fails to be statistically significant after data snooping bias adjustment (p-value = 0.1001). One clear difference between the best rule on developed and emerging markets is the number of trading signals generated by the rule. In developed markets the most profitable rule is more often than not one that generates few trading signals, and often comes from the Support and Resistance rule family. The opposite is the case in emerging markets. With a few exceptions, the most profitable rule in emerging markets is one that generated numerous trading signals (often in excess of 300) over the seven year sample period we consider. The most profitable rules in emerging markets are often short-term trading rule from the Moving Average or Filter Rule family.

The data snooping adjustment advocated by STW (1999) that we employ in this paper involves adjusting the statistical significance of the most profitable trading rule to account for the universe of rules from which it is selected. As the size of the universe increases, the STW (1999) data snooping adjusted p-value declines. We investigate whether we are unfairly penalizing the best performing trading rule in each market by comparing it to a large number of unprofitable rules. We proceed as follows: Firstly, we select the best performing trading rule for a market from all 5,806 rules run. We then calculate the STW (1999) p-value based on that rule being the only one in the universe, based on there being two rules in the universe, based on there being three rules in the universe and so on up to a rule universe of 5,806. We add the most profitable rules first so as to give the best performing rule the most chance of remaining profitable as the rule universe increases.

We display the results of this analysis for Hong Kong in Figure 1. We choose Hong Kong because the best performing rule in this market has the lowest nominal p-value out of the best performing rules in all developed markets. In other words, the most profitable rule in Hong Kong goes from being highly statistically significant prior to any adjustment for data snooping (p-value = 0.018) to highly insignificant after the entire rule universe is included in the data snooping adjustment procedure (p-value = 0.478). Figure 1 reveals that the best performing trading rule in Hong Kong becomes insignificant at the 10% level after just 6 rules are added to the rule universe. This indicates that data snooping bias is a big issue in our tests. In other words, the best performing rule is not losing its statistically significance after adjustment for data snooping bias simply because a large universe of rules is being included in the data snooping test.

[Insert Figure 1 About Here]

Each technical trading rule generates both long and short signals so we conclude by investigating the possibility that the performance of technical trading rules is not uniform across the long and short signals they generate. The results, including the average period return, the average return per trade, the average number of periods per trade, and the proportion of trades that are winning trades, are presented in Table 4. Short trades seem to be more profitable than long trades in developed markets, with the average period return being higher for short trades in 15 of the 23 developed countries. It is also clear that long trades tend to spend a lot longer in the market on average in developed countries.

The emerging market results presented in Panel B indicate long trades tend to be more profitable than short trades in emerging markets. The average period return is larger long trades in 20 of the 26 markets. There is also the trend of long trades spending more time in the market, although this result is not as strong as it was in developed markets.

[Insert Table 4 About Here]

In summary, we conclude that there is some evidence that long trades are more profitable in emerging markets and short trades are more profitable in developed market based on the optimal trading rule in each market. However, it must be remembered that the optimal trading rule in each market does not produce profits that are statistically significant beyond that which might be expected by chance given the possibility of data snooping.

5. Conclusions

We investigate the profitability of technical trading rules in the 49 developed and emerging markets that comprise the Morgan Stanley Capital Index (MSCI). In do so we suggest that we make several contributions. We consider in excess of 5,000 trading rules using two alternative bootstrapping techniques, with one of these allowing us to take account of possible data snooping bias. To the best of our knowledge, we are the first to consider the same vast universe of trading rules using the most robust methodologies in such a wide range of developed and emerging markets. This enables us to make important comparisons of profitability across markets.

We find no evidence that the profits to the technical trading rules we consider are greater than those that might be expected due to random data variation, once we take account of data snooping bias. There is some evidence that technical analysis works better in emerging markets, which is consistent with the literature that documents that these markets are less efficient, but this is not a strong result.

We suggest that our results imply that simple technical trading rules do not consistently add value when applied to a broad range of international markets. We cannot rule out the possibility that technical analysis can be used to compliment other investment techniques, or that trading rules other than the ones we examine are profitable. However, we can say that over 5,000 popular technical trading rules do not appear to add value, beyond that which may be explained by chance, when used in isolation.

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Table 1: Summary Statistics

Panel A: Developed Markets						Panel B: Emerging Markets					
	N	Mean	Std.Dev	Skew	Kurt		N	Mean	Std.Dev	Skew	Kurt
Australia	1825	0.08%	1.13%	-0.40	3.36	Argentina	1825	0.08%	2.43%	-1.02	19.51
Austria	1825	0.10%	1.12%	-0.37	2.25	Brazil	1825	0.13%	2.06%	-0.07	2.69
Belgium	1825	0.05%	1.23%	0.05	4.77	Chile	1825	0.08%	1.10%	-0.42	1.59
Canada	1825	0.06%	1.07%	-0.47	2.69	China	1825	0.10%	1.67%	-0.14	2.82
Denmark	1825	0.07%	1.12%	-0.38	2.70	Colombia	1825	0.18%	1.65%	0.26	14.67
Finland	1825	0.04%	2.15%	-0.31	5.75	Czech Republic	1825	0.15%	1.48%	-0.12	2.29
France	1825	0.04%	1.31%	-0.12	2.45	Egypt	1825	0.15%	1.64%	0.16	4.46
Germany	1825	0.05%	1.47%	-0.12	2.67	Hungary	1825	0.11%	1.62%	-0.17	1.51
Greece	1716	0.08%	1.28%	-0.11	2.85	India	1825	0.12%	1.47%	-0.51	4.74
Hong Kong	1825	0.05%	1.18%	-0.20	3.49	Indonesia	1825	0.15%	1.96%	-0.40	6.95
Ireland	1825	0.04%	1.26%	-0.53	3.67	Israel	1825	0.03%	1.36%	-0.06	4.05
Italy	1825	0.04%	1.13%	-0.26	2.95	Jordan	1825	0.10%	1.18%	-0.38	7.61
Japan	1825	0.02%	1.33%	-0.13	1.68	Korea	1825	0.12%	1.82%	-0.14	2.86
Netherlands	1825	0.04%	1.36%	-0.16	3.77	Malaysia	1825	0.07%	0.93%	-0.39	6.11
New Zealand	1825	0.08%	1.15%	-0.50	3.37	Mexico	1825	0.10%	1.44%	-0.06	2.35
Norway	1825	0.09%	1.39%	-0.47	2.58	Morocco	1825	0.08%	0.99%	0.01	3.19
Portugal	1825	0.05%	0.99%	-0.24	1.77	Pakistan	1825	0.13%	1.72%	-0.02	2.94
Singapore	1825	0.06%	1.19%	-0.13	2.92	Peru	1825	0.15%	1.52%	-0.34	3.12
Spain	1825	0.07%	1.29%	0.04	2.03	Philippines	1825	0.07%	1.54%	0.99	12.96
Sweden	1825	0.05%	1.67%	-0.04	3.18	Poland	1825	0.08%	1.64%	0.06	0.82
Switzerland	1825	0.04%	1.12%	-0.09	3.97	Russia	1825	0.15%	2.04%	-0.26	3.31
U.K.	1825	0.04%	1.12%	-0.22	2.64	South Africa	1825	0.09%	1.54%	-0.34	1.79
USA	1825	0.02%	1.06%	0.16	3.07	Taiwan	1825	0.05%	1.59%	0.05	1.72
						Thailand	1825	0.11%	1.63%	-0.27	8.33
						Turkey	1825	0.12%	3.22%	0.07	8.26
						Venezuela	1825	0.09%	2.97%	0.54	42.46

Table 1 contains summary statistics for each data series.

Table 2: Brock et al (1992) Bootstrap Results

Panel A: Developed Markets				Panel B: Emerging Markets			
	BLL Count				BLL Count		
	1%	5%	10%		1%	5%	10%
Australia	25	110	261	Argentina	70	557	1293
Austria	62	211	371	Brazil	87	509	1061
Belgium	38	234	454	Chile	291	695	1075
Canada	66	340	671	China	32	244	570
Denmark	28	270	762	Colombia	196	739	1250
Finland	15	127	321	Czech Republic	20	148	297
France	37	150	461	Egypt	111	648	1239
Germany	49	298	647	Hungary	97	481	840
Greece	67	294	742	India	110	592	979
Hong Kong	36	318	748	Indonesia	329	884	1254
Ireland	29	268	762	Israel	92	586	1136
Italy	32	205	471	Jordan	130	641	1411
Japan	14	90	186	Korea	4	64	162
Netherlands	48	167	365	Malaysia	134	618	1066
New Zealand	14	113	315	Mexico	38	170	356
Norway	21	169	414	Morocco	105	327	766
Portugal	220	829	1258	Pakistan	208	737	1122
Singapore	55	260	545	Peru	18	119	304
Spain	26	183	440	Philippines	94	409	911
Sweden	32	179	482	Poland	103	357	594
Switzerland	23	171	325	Russia	57	281	554
U.K.	12	102	361	South Africa	14	174	393
USA	30	188	440	Taiwan	29	154	414
				Thailand	25	139	380
				Turkey	18	252	563
				Venezuela	21	151	285

Table 2 contains the bootstrap results for each country based on the Brock et al. (1992) approach. The number of rules (out of the universe of 5,806) that are statistically significant at the 1%, 5%, and 10% levels respectively. For a rule to be statistically significant at a given level, say 5%, it must produce greater profits on the randomly generated bootstrapped series than the original series less then 5% of the time.

Table 3: Sullivan et al (1999) Bootstrap Results – All Trades

Panel A: Developed Markets

	Nominal p-Value	STW p-Value	Average Daily Return	Average Return Per Trade	Total No. of Trades	No. of Winning Trades	No. of Losing Trades	Average Days Per Trade
Australia	0.288	0.996	0.08%	38.16%	4	2	2	431
Austria	0.264	0.988	0.10%	45.01%	4	3	1	406
Belgium	0.070	0.816	0.08%	35.98%	4	3	1	406
Canada	0.076	0.802	0.09%	84.05%	2	2	0	894
Denmark	0.100	0.856	0.09%	40.00%	4	3	1	406
Finland	0.060	0.640	0.12%	16.21%	14	10	4	128
France	0.030	0.772	0.06%	16.91%	6	3	3	287
Germany	0.046	0.620	0.11%	24.51%	8	6	2	223
Greece	0.038	0.488	0.15%	0.39%	646	259	387	3
Hong Kong	0.018	0.478	0.11%	12.31%	17	12	5	107
Ireland	0.028	0.342	0.11%	0.37%	562	225	337	3
Italy	0.030	0.828	0.08%	68.56%	2	2	0	884
Japan	0.042	0.890	0.02%	20.77%	2	2	0	887
Netherlands	0.080	0.764	0.07%	32.27%	4	3	1	409
New Zealand	0.386	0.998	0.08%	48.46%	3	3	0	603
Norway	0.214	0.928	0.12%	3.01%	70	42	28	26
Portugal	0.032	0.438	0.10%	2.15%	88	42	46	21
Singapore	0.050	0.802	0.09%	26.97%	6	4	2	243
Spain	0.126	0.850	0.07%	67.62%	2	2	0	862
Sweden	0.026	0.436	0.14%	0.30%	861	345	516	2
Switzerland	0.058	0.786	0.07%	19.82%	6	6	0	295
U.K.	0.114	0.876	0.05%	20.97%	4	2	2	431
USA	0.044	0.794	0.04%	8.65%	8	5	3	216

Panel B: Emerging Markets								
	Nominal p-Value	STW p-Value	Average Daily Return	Average Return Per Trade	Total No. of Trades	No. of Winning Trades	No. of Losing Trades	Average Days Per Trade
Argentina	0.036	0.672	0.12%	8.60%	26	8	18	62
Brazil	0.028	0.464	0.23%	0.68%	628	269	359	3
Chile	0.004	0.116	0.17%	0.43%	701	339	362	3
China	0.056	0.678	0.16%	10.38%	28	18	10	64
Colombia	0.004	0.100	0.31%	0.75%	742	327	415	2
Czech Republic	0.294	0.986	0.15%	137.59%	2	2	0	803
Egypt	0.038	0.550	0.23%	1.11%	370	155	215	5
Hungary	0.060	0.844	0.12%	55.95%	4	3	1	431
India	0.162	0.794	0.15%	0.55%	514	238	276	4
Indonesia	0.022	0.360	0.27%	0.71%	688	324	364	3
Israel	0.016	0.298	0.12%	0.27%	834	321	513	2
Jordan	0.176	0.894	0.12%	1.56%	142	72	70	13
Korea	0.298	0.942	0.13%	0.58%	398	169	229	5
Malaysia	0.016	0.248	0.13%	0.61%	395	176	219	5
Mexico	0.430	0.984	0.09%	6.17%	28	15	13	65
Morocco	0.012	0.138	0.16%	0.47%	620	257	363	3
Pakistan	0.072	0.710	0.19%	1.56%	219	113	106	8
Peru	0.404	1.000	0.14%	129.79%	2	2	0	887
Philippines	0.032	0.366	0.16%	0.80%	363	162	201	5
Poland	0.028	0.834	0.09%	42.79%	4	3	1	431
Russia	0.232	0.922	0.18%	0.41%	812	386	426	2
South Africa	0.144	0.846	0.13%	0.92%	259	125	134	7
Taiwan	0.076	0.748	0.10%	0.60%	303	143	160	6
Thailand	0.030	0.440	0.20%	0.64%	564	251	313	3
Turkey	0.092	0.700	0.21%	0.87%	430	182	248	4
Venezuela	0.198	0.882	0.12%	2.04%	106	64	42	11

Table 3 contains the results for the Sullivan et al. (1999) bootstrap procedure. The nominal p-value is that for the best rule, unadjusted for data snooping, while the STW (1999) adjusts this p-value for data snooping. All other statistics relate to the best rule for each country.

Table 4: Sullivan et al (1999) Bootstrap Results – Profitability by Long and Short Trades

Panel A: Developed Markets – Long Trades					Panel B: Developed Markets – Short Trades				
	Avg Period Ret	Ave Ret Per Trade	Avg Periods Per Trade	Prop of Winning Trades		Avg Period Ret	Ave Ret Per Trade	Avg Periods Per Trade	Prop of Winning Trades
Australia	0.09%	72.42%	822	50%	Australia	0.10%	3.89%	41	50%
Austria	0.11%	88.24%	810	50%	Austria	0.89%	1.78%	2	100%
Belgium	0.08%	60.16%	709	50%	Belgium	0.11%	11.80%	104	100%
Canada	0.10%	139.53%	1,359	100%	Canada	0.07%	28.58%	429	100%
Denmark	0.10%	72.70%	708	50%	Denmark	0.07%	7.30%	104	100%
Finland	0.13%	22.31%	174	86%	Finland	0.13%	10.12%	81	57%
France	0.05%	28.25%	558	33%	France	0.34%	5.58%	16	67%
Germany	0.09%	34.76%	382	50%	Germany	0.22%	14.27%	64	100%
Greece	0.20%	0.58%	3	45%	Greece	0.08%	0.20%	2	35%
Hong Kong	0.09%	16.46%	174	67%	Hong Kong	0.24%	7.63%	32	75%
Ireland	0.13%	0.47%	4	45%	Ireland	0.10%	0.27%	3	35%
Italy	0.07%	112.44%	1,635	100%	Italy	0.19%	24.68%	132	100%
Japan	0.02%	40.01%	1,773	100%	Japan	1.54%	1.54%	1	100%
Netherlands	0.07%	55.57%	783	100%	Netherlands	0.25%	8.97%	36	50%
New Zealand	0.08%	68.18%	897	100%	New Zealand	0.56%	9.03%	16	100%
Norway	0.15%	5.17%	34	74%	Norway	0.05%	0.84%	17	46%
Portugal	0.11%	3.03%	27	52%	Portugal	0.09%	1.28%	14	43%
Singapore	0.11%	71.41%	673	100%	Singapore	0.17%	4.75%	28	50%
Spain	0.07%	124.20%	1,697	100%	Spain	0.41%	11.03%	27	100%
Sweden	0.17%	0.38%	2	43%	Sweden	0.11%	0.22%	2	37%
Switzerland	0.06%	34.00%	537	100%	Switzerland	0.11%	5.65%	52	100%
U.K.	0.04%	36.69%	822	50%	U.K.	0.13%	5.25%	40	50%
USA	0.03%	11.55%	412	25%	USA	0.30%	5.76%	19	100%

Panel C: Emerging Markets – Long Trades

	Avg Period Ret	Ave Ret Per Trade	Avg Periods Per Trade	Prop of Winning Trades
Argentina	0.12%	14.75%	121	8%
Brazil	0.30%	0.98%	3	52%
Chile	0.21%	0.62%	3	52%
China	0.15%	15.64%	103	64%
Colombia	0.41%	1.15%	3	52%
Czech Republic	0.17%	269.30%	1,598	100%
Egypt*	0.32%	1.80%	6	49%
Hungary	0.13%	103.05%	824	50%
India	0.21%	0.91%	4	53%
Indonesia	0.35%	1.06%	3	55%
Israel	0.14%	0.32%	2	42%
Jordan	0.17%	2.71%	16	61%
Korea	0.18%	1.02%	6	47%
Malaysia	0.17%	0.90%	5	49%
Mexico	0.11%	11.45%	103	71%
Morocco	0.22%	0.70%	3	47%
Pakistan	0.23%	2.50%	11	55%
Peru	0.15%	254.34%	1,754	100%
Philippines	0.21%	1.09%	5	50%
Poland	0.09%	78.15%	852	50%
Russia	0.26%	0.69%	3	52%
South Africa	0.15%	1.47%	10	53%
Taiwan	0.11%	0.74%	7	50%
Thailand	0.27%	0.93%	4	48%
Turkey	0.24%	1.13%	5	48%
Venezuela	0.29%	3.06%	11	62%

Panel D: Emerging Markets – Short Trades

	Avg Period Ret	Ave Ret Per Trade	Avg Periods Per Trade	Prop of Winning Trades
Argentina	0.57%	2.45%	4	54%
Brazil	0.15%	0.38%	3	34%
Chile	0.12%	0.25%	2	44%
China	0.20%	5.11%	25	64%
Colombia	0.17%	0.35%	2	36%
Czech Republic	0.74%	5.89%	8	100%
Egypt*	0.10%	0.42%	4	35%
Hungary	0.23%	8.85%	39	100%
India	0.07%	0.18%	3	40%
Indonesia	0.16%	0.36%	2	39%
Israel	0.10%	0.22%	2	35%
Jordan	0.04%	0.40%	10	41%
Korea	0.04%	0.14%	3	38%
Malaysia	0.08%	0.32%	4	40%
Mexico	0.03%	0.89%	27	36%
Morocco	0.09%	0.24%	3	36%
Pakistan	0.11%	0.62%	6	48%
Peru	0.26%	5.23%	20	100%
Philippines	0.11%	0.51%	5	39%
Poland	0.71%	7.43%	11	100%
Russia	0.07%	0.13%	2	43%
South Africa	0.09%	0.38%	4	43%
Taiwan	0.09%	0.46%	5	45%
Thailand	0.12%	0.36%	3	41%
Turkey	0.16%	0.62%	4	37%
Venezuela	0.10%	1.06%	11	59%

Table 4 contains performance statistics for the short trades signalled by the best rule for each country.

Figure 1: Changes in STW p-value for Hong Kong as Rule Universe Increases