Technical Analysis Around the World

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JEL Classification: G12, G14
Keywords: Technical Analysis, Quantitative, Market Timing

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Abstract

Over 5,000 popular technical trading rules are not consistently profitable in the 49 country indices that comprise the Morgan Stanley Capital Index once data snooping bias is accounted for. Each market has some rules that are profitable when considered in isolation but these profits are not statistically significant after data snooping bias adjustment. 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 these trading rules compliment 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 during the time period we consider.

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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. 1653) describing it as "pervasive." These two factors have resulted in a large amount of research energy being devoted to investigating whether technical trading rules are profitable. Most empirical studies find that technical analysis does not add value in the US equity market, but several authors (e.g. Bessembinder and Chan, 1995; Ito, 1999) have presented supportive evidence in emerging markets. More recently, Zhu and Zhou (2009) develop a theoretical model that shows that moving average rules can add value to other asset allocation rules.

We add to the literature by investigating the profitability of technical trading rules in the 49 developed and emerging market indices that make up the Morgan Stanley Capital Index (MSCI). In doing so, we make several contributions. Firstly, we consider in excess of 5,000 trading rules from four different rule families on each market.[2] Most previous studies

[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.

[2] We follow the majority of authors and study "mechanical" technical trading rules. Jegadeesh (2000) and Taylor (2003) find pattern based rules, such as those studied by Lo, Mamaysky, and Wang (2000) and Dawson and Steeley (2003), are not profitable. This has led Taylor (2003) to suggest that future research should focus on mechanical rules, as we do in this study.

consider a smaller number of rules[3] and, to the best of our knowledge, no other study uses a consistent framework across a large number of markets. This is important as while it is generally accepted that technical analysis has not been profitable in the US equity market in the last decade[4] the question of the profitability of technical analysis in a large number of developed and emerging markets has not been addressed. The finding of Chaudhuri and Wu (2003) that the random walk hypothesis does not hold in a number of emerging markets raises the possibility that technical analysis is still profitable in these markets. Moreover, while there is evidence showing technical analysis is profitable in emerging markets in early periods, results are often inconsistent across different studies. For instance, Parisi and Vasquez (2000) find variable moving average (VMA) rules are profitable in Chile yet Ratner and Leal (1999) find these same rules are not consistently profitable in Chile, Bessembinder and Chan (1995) find short-term VMA rules are profitable in Japan whereas Ratner and Leal (1999) find the opposite. Ito (1999) finds VMA rules add value in Indonesia, yet Ratner and Leal (1999) find they do not.[5] However, none of these papers account for data snooping bias so it is difficult to relate these results to those documented for the US.

Secondly, we carefully choose an appropriate data set and sample period. We use MSCI daily data from when it first became available in 2001 to 2007. It is well established that the profitability of technical analysis has declined over time (e.g. Sullivan, Timmermann,

[3] Exceptions to this include Sullivan, Timmermann, and White (1999) who consider five rule families and over 7,000 individual rules in the US equity market, Hsu and Kuan (2010) who investigate over 39,000 rules from 15 rule families in US equity indices, and Hsu, Hsu, and Kuan (2010) who use two rule families and in excess of 16,000 individual rules on three US equity indices and six emerging market equity indices and ETFs.

[4] See Hsu, Hsu, and Kuan (2008) and Bajgrowicz and Scaillet (2009).

[5] See Parisi and Vasquez (2000) Table 1, Bessembinder and Chan (1995) Table 2, and Ratner and Leal (1999) Table 2, and Ito (1999) Table 4. We use the term “profitable” to denote a finding of a difference in returns following buy and sell signals that is statistically significant.

and White, 1999; Bajgrowicz and Scaillet, 2009) so it makes little sense to include a long sample period. Rather, a recent period is likely to be of the most interest to the academic and investment communities. The importance of international markets to portfolio managers continues to increase. A recent survey finds the average allocation of money to international markets by global funds was 57 percent in 2006 compared with just 37 percent in 2002.[6] 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. We use MSCI index data rather than ETFs themselves as MSCI index data covers all markets whereas ETF data does not.

The methodological aspects of measuring technical trading rule profitability, and correctly accounting for data snooping bias, is a literature in its own right. We do not attempt to add to this literature, but rather follow the most commonly used technique, which is that of Sullivan, Timmermann, and White (1999). This method is based on the White (2000) Reality Check (RC) approach. Subsequent researchers have attempted to improve this methodology. Hansen (2005) shows the RC approach can be affected by the inclusion of irrelevant rules and develops a "Superior Predictive Ability" (SPA) test that overcomes this issue. However, as noted by Hsu, Hsu, and Kuan (2010), both the RC and SPA tests do not identify all significant rules. Romano and Wolf (2005) develop a RC-based step-wise test that identifies all significant rules, but as Hsu, Hsu, and Kuan (2010) state, this still suffers from the irrelevant rule inclusion issue. Hsu, Hsu, and Kuan (2010) therefore develop a SPA-based step-wise test. More recently, Bajgrowicz and Scaillet (2009) develop a "False Discovery Rate" test

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

which assumes that investor bases their decisions on a portfolio of strategies rather than a single strategy. Despite the differences in methodologies, studies that apply multiple methodologies using rules similar to those in this paper and financial data typically find their conclusions hold regardless of the technique adopted. The interested reader should refer to Qi and Wu (2006) for a study that uses the RC and SPA approaches and Bajgrowicz and Scaillet (2009) for a paper that uses the RC test, the RC-based step-wise test, and the False Discovery Rate test.[7]

As well as the standard Sullivan, Timmermann, and White (1999) RC approach, we present two other types of results for robustness. To address concerns regarding the inclusion of irrelevant rules issue, we follow Marshall, Cahan, and Cahan (2008) and generate results that address the question "how many rules can be included in the universe before the best performing rule loses its post-data snooping adjustment statistical significance?" We also apply the popular Brock, Lakonishok, and LeBaron (1992) bootstrapping methodology which simply shows whether a given rule generates returns that differ from those associated with a given null model of returns. This approach takes no account of data snooping bias so its inclusion gives the reader a perspective on just how many rules are profitable prior to data snooping bias adjustment. The Brock, Lakonishok, and LeBaron (1992) methodology has been used by the majority of previous technical analysis studies on international markets that consider a sub-sample of the rules we include in this study[8] so its inclusion also allows the reader to compare our results with previous international technical analysis studies.

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[7] Qi and Wu (2006) find that trading rule profitability is much weaker in their most recent sub-period based on both the RC and SPA methodologies. Bajgrowicz and Scaillet (2009) show the FDR technique is more powerful than the RC or RC-based step-wise test, but even though it identifies more well-performing rules in sample, the performance of these rules is not persistent out-of-sample.

[8] For instance, Bessembinder and Chan (1995), Ito (1999), Parisi and Vasquez (2000), and Ratner and Leal (1999).

We find that some 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 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.[9] 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. Data, Trading Rule Specifications, and Methodology

2.1. 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 these results are

[9] 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 Timmermann, and White (1999). We provide detailed explanations of these rules in Section 2.

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 are available for the MSCI for each country. We suggest that the focus on data for a recent time period is appropriate as Sullivan, Timmermann, and White (1999) and Bajgrowicz and Scaillet (2009) have shown that the returns to technical analysis have declined over time. This means that documenting profits on more historical series is less relevant to academics and practitioners alike.

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. Colombia 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 2.3.

[Insert Table 1 About Here]

2.2. Trading Rule Specifications

We apply 5,806 of the technical trading rules suggested by Sullivan, Timmermann, and White (1999). Sullivan, Timmermann, and White (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. Sullivan, Timmermann, and White (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 positions when price decreases (increases) by x% from a subsequent high (low). We test these rules and two variations. Following Sullivan, Timmermann, and White (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. The interest reader should also refer to Corrado and Lee (1992) for a good discussion on filter rules.

Moving Average rules generate buy (sell) signals when the price or a short moving average moves above (below) a long moving average. We follow Sullivan, Timmermann, and White (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 pre-specified number of periods, d, before the signal is acted upon. A final variation we consider is holding a position for a pre-specified 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 Sullivan, Timmermann, and White (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 Sullivan, Timmermann, and White (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.

2.3. Methodology

There is much debate over the most appropriate way to account for data snooping bias when measuring the profits of technical trading rules. However, studies that use different methodologies on the rules we test (e.g. Qi and Wu, 2006; Bajgrowicz and Scaillet, 2009) typically reach similar conclusions regardless of the methodology used. As the contribution of our paper is not to develop a new data snooping methodology, we adopt the most popular data snooping methodology, which is that of Sullivan, Timmermann, and White (1999). This method has been criticized as being overly sensitive to the inclusion of underperforming rules in the rule universe so we follow Marshall, Cahan, and Cahan (2008) and check how sensitive our conclusions are to the size of the rule universe.

In accordance with Sullivan, Timmermann, and White (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 return at time *t*. Sullivan, Timmermann, and White (1999) note that there are two alternative benchmark returns that can be used. The first is zero which represents an approach that is always out of the market. The second is the market index return which represents a long buy-and-hold position in the market index. We use the market index return as the benchmark. 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 Sullivan, Timmermann, and White (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.,

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

Following Sullivan, Timmermann, and White (1999) we use a stationary bootstrap of on the *M* values of $\bar{f}_k$ to test the null hypothesis.[10] 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 Sullivan, Timmermann, and White (1999), we set *B* = 500. For the *k-th* rule, this results in *B* means being generated, which we denote $\bar{f}^*_{k,b}$ $(b = 1,\dots,B)$, from the *B* re-sampled time-series, where:

$$\bar{f}^*_{k,b} = \sum_{t=1}^{T} f^*_{k,t,b} / T, \quad (b = 1,\dots,B). \tag{2}$$

The test two statistics employed in the test are:

[10] The interested reader should consult Appendix C of Sullivan, Timmermann, and White (1999) for more details.

$$\overline{V}_M = \max_{k=1,...,M} [\sqrt{T}\,\bar{f}_k] \tag{3}$$

and

$$\overline{V}^*_{M,b} = \max_{k=1,...,M} [\sqrt{T}\,(\bar{f}^*_{k,b} - \bar{f}_k)] \quad , \quad (b = 1,..., B). \tag{4}$$

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.

Our second methodology is based on that of Brock, Lakonishok, and LeBaron (1992). This 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. Brock, Lakonishok, and LeBaron (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 (2008) and use the GARCH-M null model which we present in equations 5 to 7 (see Brock, Lakonishok, and LeBaron, 1992, for a detailed description of this model):

$$r_t = \alpha + \gamma\sigma_t^2 + \beta\varepsilon_{t-1} + \varepsilon_t \tag{5}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

$$\varepsilon_t = \sigma_t z_t \qquad z_t \sim N(0,1) \tag{7}$$

The basic premise behind the Brock, Lakonishok, and LeBaron (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 Brock, Lakonishok, and LeBaron (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. 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. We include results based on the Brock, Lakonishok, and LeBaron (1992) methodology for at least two reasons. Firstly, this is the approach used by the majority of international technical trading rule studies, which means its inclusion allows the reader to relate our results to early work. Secondly, these results highlight how rules are profitable prior to adjustment for data snooping bias and therefore highlight the extent of this issue.

3. Results

Our results indicate there is no evidence that the technical trading rules we consider consistently add value in our sample period 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 Brock, Lakonishok, and LeBaron (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 Brock, Lakonishok, and LeBaron (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 Sullivan, Timmermann, and White (1999) bootstrap techniques. Unlike the Brock, Lakonishok, and LeBaron (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 Sullivan, Timmermann, and White (1999) to generate the nominal p-value is different to the Brock, Lakonishok, and LeBaron (1992) procedure. The Sullivan, Timmermann, and White (1999) 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 Sullivan, Timmermann, and White (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 Brock, Lakonishok, and LeBaron (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 Brock, Lakonishok, and LeBaron (1992) technique. While there may be some differences between the results generated by the Brock, Lakonishok, and LeBaron (1992) and Sullivan, Timmermann, and White (1999) techniques prior to data snooping bias adjustment, the result after this adjustment 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 Sullivan, Timmermann, and White (1999) 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 Sullivan, Timmermann, and White (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 Sullivan, Timmermann, and White (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 Sullivan, Timmermann, and White (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 I. 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 I 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 statistical significance after adjustment for data snooping bias simply because a large universe of rules is being included in the data snooping test.

[Insert Figure I 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 market indices that comprise the Morgan Stanley Capital Index (MSCI). In doing so we suggest that we make several contributions. We consider in excess of 5,000 trading rules from four rule families on each market. This allows us to determine if, unlike the well-documented US result, technical adds value around the world. There is evidence that emerging markets do not follow a random walk and previous authors have documented profits to technical analysis in some emerging markets in earlier periods. However, this evidence is often inconsistent across different studies. We focus on a recent time period to ensure the profitability we document is not driven by historical periods that are of less interest to academics and practitioners alike.

We find that a number of trading rules generate profits when considered in isolation. However, there is 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 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 in the time period we consider.

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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
UK	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. Mean is the average daily return over the 2001 – 2007 period. Std. Dev. is the standard deviation of daily returns. Skew represents skewness, while Kurt refers to kurtosis.

Table 2: Brock, Lakonishok, and LeBaron (1992) Bootstrap Results

Panel A: Developed Markets				Panel B: Emerging Markets			
	Number Significant				Number Significant		
	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
UK	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, Lakonishok, and LeBaron (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 than 5% of the time.

Table 3: Sullivan, Timmermann, and White (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
UK	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, Timmermann, and White (1999) bootstrap procedure. The nominal p-value is that for the best rule, unadjusted for data snooping, while the STW procedure adjusts this p-value for data snooping. All other statistics relate to the best rule for each country.

Table 4: Sullivan, Timmermann, and White (1999) Bootstrap Results – Profitability by Long and Short Trades

Panel A: Developed Markets – Long Trades					Panel B: Developed Markets – Short Trades				
	Avg Daily Ret	Avg Ret Per Trade	Avg Days Per Trade	Prop of Winning Trades		Avg Daily Ret	Avg Ret Per Trade	Avg Days 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%
UK	0.04%	36.69%	822	50%	UK	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					Panel D: Emerging Markets – Short Trades			
	Avg Daily Ret	Avg Ret Per Trade	Avg Days Per Trade	Prop of Winning Trades		Avg Daily Ret	Avg Ret Per Trade	Avg Days Per Trade	Prop of Winning Trades
Argentina	0.12%	14.75%	121	8%	Argentina	0.57%	2.45%	4	54%
Brazil	0.30%	0.98%	3	52%	Brazil	0.15%	0.38%	3	34%
Chile	0.21%	0.62%	3	52%	Chile	0.12%	0.25%	2	44%
China	0.15%	15.64%	103	64%	China	0.20%	5.11%	25	64%
Colombia	0.41%	1.15%	3	52%	Colombia	0.17%	0.35%	2	36%
Czech Republic	0.17%	269.30%	1,598	100%	Czech Republic	0.74%	5.89%	8	100%
Egypt	0.32%	1.80%	6	49%	Egypt	0.10%	0.42%	4	35%
Hungary	0.13%	103.05%	824	50%	Hungary	0.23%	8.85%	39	100%
India	0.21%	0.91%	4	53%	India	0.07%	0.18%	3	40%
Indonesia	0.35%	1.06%	3	55%	Indonesia	0.16%	0.36%	2	39%
Israel	0.14%	0.32%	2	42%	Israel	0.10%	0.22%	2	35%
Jordan	0.17%	2.71%	16	61%	Jordan	0.04%	0.40%	10	41%
Korea	0.18%	1.02%	6	47%	Korea	0.04%	0.14%	3	38%
Malaysia	0.17%	0.90%	5	49%	Malaysia	0.08%	0.32%	4	40%
Mexico	0.11%	11.45%	103	71%	Mexico	0.03%	0.89%	27	36%
Morocco	0.22%	0.70%	3	47%	Morocco	0.09%	0.24%	3	36%
Pakistan	0.23%	2.50%	11	55%	Pakistan	0.11%	0.62%	6	48%
Peru	0.15%	254.34%	1,754	100%	Peru	0.26%	5.23%	20	100%
Philippines	0.21%	1.09%	5	50%	Philippines	0.11%	0.51%	5	39%
Poland	0.09%	78.15%	852	50%	Poland	0.71%	7.43%	11	100%
Russia	0.26%	0.69%	3	52%	Russia	0.07%	0.13%	2	43%
South Africa	0.15%	1.47%	10	53%	South Africa	0.09%	0.38%	4	43%
Taiwan	0.11%	0.74%	7	50%	Taiwan	0.09%	0.46%	5	45%
Thailand	0.27%	0.93%	4	48%	Thailand	0.12%	0.36%	3	41%
Turkey	0.24%	1.13%	5	48%	Turkey	0.16%	0.62%	4	37%
Venezuela	0.29%	3.06%	11	62%	Venezuela	0.10%	1.06%	11	59%

Table 4 contains performance statistics for the long and short trades signalled by the best rule for each country. “Avg Daily Ret” is the average daily return, “Avg Ret Per Trade” is the average return per trade, “Avg Days Per Trade” is the average time a trade is open in days, while “Prop of Winning Trades” is the proportion of trades that are profitable.

Figure I: Changes in Sullivan, Timmermann, and White (1999) p-value for Hong Kong as Rule Universe Increases