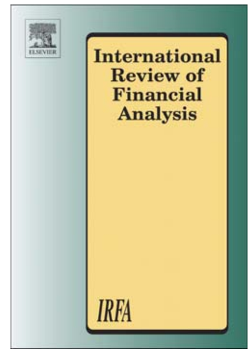

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How profitable are FX technical trading rules?

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Abstract

This paper provides a comprehensive empirical investigation of the profitability of foreign exchange technical trading rules over the 1996:10 - 2015:06 period for 22 currencies quoted in US dollars. It reports evidence of profitability across a universe of 113,148 rules that include traditional moving average rules and those constructed on the basis of technical indicators such as Bollinger bands and the relative strength index. The best trading rules achieve annualised returns of up to 30%. The Step-SPA test (Hsu et al., 2010) results show a sharp fall in the total number of rules that are robust to data snooping bias. Virtually no traditional rule is significant in the 2006-2015 sub-sample, in line with the adaptive markets hypothesis. By contrast, rules based on new technical indicator such as Bollinger Band and relative strength index rules remain robustly profitable across all currencies over the more recent sub-sample.

Key Words: *Data Snooping, Foreign Exchange, Technical Trading, Stepwise SPA test*

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1. Introduction

Technical analysis refers to making investment decisions on the basis of historical price and other market data such as turnover. Its widespread use in foreign exchange (FX) markets has been confirmed by surveys (Taylor and Allen, 1992; Menkhoff, 1997; Lui and Mole, 1998; Oberlechner, 2001; Gehrig and Menkhoff, 2004; Menkhoff and Taylor 2007). Evidence supporting the profitability of technical trading rules (TTRs) in the FX markets dates from the late 1980s (Sweeney, 1986; Levich and Thomas, 1993; Neely, 1997; Le Baron, 1999, 2002). As technical analysis relies mainly on past information, TTR profitability poses a challenge to the efficient markets hypothesis (EMH).

TTR profitability for at least for some currencies over particular periods cannot be explained by standard risk factors (Neeley and Weller, 2012). This is difficult to reconcile with the two distinctive characteristics of FX markets. First, the global FX market is highly liquid and total turnover is several times greater than the combined daily turnover of the largest stock exchanges (Menkhoff and Taylor, 2007). Second, Sager and Taylor (2006) stress that FX markets are dominated almost exclusively by professional traders which should mitigate against the influence of retail investor sentiment. The implication is that FX markets should be efficient.

This paper contributes to the literature in two respects. Researchers (Levich and Thomas, 1993; LeBaron, 2002; Qi and Wu, 2006; Kuang et al., 2010) have pointed out that that TTR profitability might be the result of data-snooping bias that traditionally has been ignored. Thus the first contribution is that it evaluates whether TTR profitability is robust to data snooping. If it is not found to be robust, then the challenge to the EMH falls. The statistical robustness of our results is checked by using the powerful new Step-SPA test developed by Hsu et al. (2010). The early White (2000) Reality Check (RC) test is conservative because the null distribution of the test statistic is obtained under the least favourable (to the alternative hypothesis) configuration. Hansen's (2005) Superior Predictive Ability (SPA) test enjoys two advantages over the RC test. Not only it is more powerful but also it is less sensitive to the inclusion of poor and irrelevant alternatives by which the RC test may be manipulated.

However, while both the RC and the SPA can only indicate whether at least one rule violates the null hypothesis, the Step-SPA test is highly consistent as it can identify the violated null hypothesis with probability almost equal to one, and its family-wise error rate can be asymptotically controlled at any pre-specified level. Hsu et al. (2010) showed analytically and with simulations that the Step-SPA test is more powerful than the stepwise version of the RC test by Romano and Wolf (2005). The above testing techniques have also been used in recent studies on technical analysis applied to equity markets. This literature includes the early studies of Hsu and Kuan (2005) and Marshall, Cahan and Cahan (2008) and the more recent investigations of Shynkevich (2012a, 2012b, 2012c).

The second contribution of the paper is that, given the extant evidence on TTR profitability, it explicitly considers an alternative to the EMH. It tests Lo's (2004) adaptive markets hypothesis (AMH) which Neeley and Weller (2012) adduce as the most plausible explanation of TTR profitability. Neeley, Weller and Ulrich (2009) point to three AMH predictions in the context of TTRs in FX markets. First, profitable TTR opportunities will generally be found in financial markets. Second, learning and competition will gradually erode these opportunities over time. Third, more complex TTR strategies will persist for longer than simpler ones.

This paper evaluates the profitability of a total of 113,148 rules on a cross section of 22 currencies quoted in US dollars using daily data over the 1997:10 to 2015:06 period. Both the number of currencies included in our sample and the size of the universe of TTRs are larger than those employed in the literature to date. The universe of rules comprises both traditional and novel rules. The former category includes moving average (arithmetic, exponential and triangular), channel breakout, trading range break, and filter rules. The latter category includes rules based on technical indicators such as Bollinger bands and the relative strength index (RSI). This is one of the first papers to employ such rules in a study of technical analysis in FX markets. Moreover, our dataset is more comprehensive and consistent than that of other recent data snooping studies on the performance of TTRs in the FX market (Qi and Wu, 2006; Kuang et al. 2010).

Our findings suggest that prior to controlling for data-snooping bias, TTRs perform well and achieve profits of up to 29.7% pa. Controlling for data snooping, the results show a large decrease in the number of significant trading rules with a sharp divergence between the performance of traditional and new TTRs. The results show that that no traditional TTRs are significant, with *p*-values very close to 1. These are in line with the literature suggesting that the performance of these trading rules has decreased over the past two decades (LeBaron 2002; Neely, Weller and Ulrich, 2009) and with recent studies (Qi and Wu, 2006; Kuang et al., 2010). However the new rules based on technical trading signals yield very different results. After controlling for data snooping, we find a number of robust trading rules for some 18 currencies and particularly for advanced economy currencies.

Finally we point to some caveats of this study. The first is that it only considers quantitative technical analysis and ignores chartism due to the difficulties in parameterizing consistent chartist strategies. Second, it only tests single static TTRs when in practice technicians can employ multiple and dynamic strategies as in Neeley and Weller (2012). The upshot of these caveats is to place a higher burden of proof on the profitability of TTRs. Thus any finding of robustly profitable TTRs would constitute strong evidence against the EMH. The paper proceeds as follows. Section 2 describes the data and outlines methodology employed. Section 3 presents our empirical results while a final section concludes.

2. Data and Methodology

2.1 Data

We collected daily spot exchange rates for 22 currencies quoted against the US dollar from the WM company/Reuters dataset on Datastream. The sample currencies include those for Australia, Canada, Czech Republic, Denmark, Euro zone, Hong Kong, Hungary, India, Israel, Japan, Latvia, Lithuania, New Zealand, Norway, Philippines, Poland, Russia, Singapore, South Africa, Sweden, Switzerland, and the United Kingdom. The data extend from October 1997 to end of June 2015 for most currencies (those for the Euro, Israel, Latvia, Lithuania, Poland and Russia start later) and includes observations on all business days. The starting point of the data was determined by the availability of one-day forward data. We employed the latter rather than interest rate data as a consistent measure of the interest rate differential following Menkhoff et al. (2012a, 2012b). Table A.1 in the Appendix reports the currency code, the data span and the mean and standard deviation of forward discount and excess returns for each currency.

2.2 Universe of trading rules

The empirical analysis involves 113,148 trading rules which, to our knowledge, is the largest set of TTRs tested on such a wide cross section of currencies. They can be divided into traditional TTRs (such as moving averages) and newer TTRs based on technical indicators such as Bollinger bands. While the former have been widely investigated, the latter have been little studied previously despite being popular among practitioners. Appendix A provides a summary of the parameters used in the calibration of trading rules.

Bollinger Bands (BB) can be used as a standalone to create trading signals or in conjunction with other technical indicators (Bollinger, 2001). The indicator comprises of three time series: the middle band which is a measure of the intermediate-term trend (a simple moving average) and an upper and lower band. The interval between the outer and middle bands is determined by volatility, typically the standard deviation of the same data that were used for the moving average. The bands provide a relative high/low for FX over a given period of time. Exchange rates are considered to be high when they hit the upper band and low when they meet the lower band. A buy signal is generated when the exchange rate crosses the lower band from above by *b%* (then prices are considered to be low) and a sell signal when the exchange rate cuts the upper band from below by *b%*.

The Relative Strength Index (RSI) can be classified as a reversal or contrarian indicator (Wilder, 1978).[1] It is computed as the ratio of higher closes to lower closes. The indicator is measured on a scale from 0 to 100, with high and low levels marked at 60 or above and 40 or below, respectively. When the RSI index is *b%* above (below) the high (low) level, one buys (sells) the foreign currency.

Moving Average Convergence/Divergence (MACD) is a trend following momentum indicator introduced by Appel (1999). This technical indicator not only gives the momentum of a particular currency but also a measure of the duration of a trend and an indication of whether a currency is overbought/oversold. It is computed as the difference between the 26-day and the 12-day exponential moving average (EMA) of exchange rates. This difference is charted over time alongside its moving average (the MACD-line). The MACD-line is always accompanied by the signal rule which is a 9-day EMA. We focus on the simplest MACD rule that generates trading signals on the crossover between the MACD-line and the signal line or the crossover with 0. An upwards move is called a bullish crossover and a downwards move a bearish crossover. They both indicate that the trend in the currency is about to accelerate in the direction of the crossover. A crossing of the MACD-line through zero occurs when there is no difference between fast (12-day) or slow (26-day) EMAs. Zero line crossovers provide evidence of a change in the direction of a trend but provide less confirmation of its momentum than a signal line crossover.

[1] We are grateful to an anonymous reviewer for clarifying this point.

2.3 Excess Returns

We compare the relative performance of TTRs using average annualised excess returns as the profitability criterion. We assume that the investor can fund her position foreign currency position using USDs and is able to open a new position only if the previous position is closed. Following Menkhoff et al. (2012a, 2012b), the log excess return (*rx*) from a foreign currency ε for an US investor is given by:

$$rx_t = i_{t-1} - i_{t-1} - \Delta s_t \approx f_{t-1} - s_t \quad (1)$$

where *i* is the overnight or daily interest rate, and *s* and *f* denote spot and forward exchange rates in logs, respectively. The forward discount is equivalent to interest rate differentials since covered interest parity holds closely in the data at the daily frequency (Akram, Rime, and Sarno, 2008). It is employed instead of interest rate differentials due to the non-availability of consistent data across currencies on the latter. The investor always has to roll or close the one-day forward contract but does not always have to open or close a position in the spot market. We assume that the investor has to close all positions in the final sample month, June 2015. Finally, given that the only available (BBI/Reuters) bid-ask spreads are based on indicative quotes and hence "too high" (Lyons, 2001), we do not use transaction costs which are recognise as being quite narrow for large FX trades.

2.4 Bootstrap Snooper

Data-snooping bias can be tested for in many ways but some of these methods can be impractical when the number of hypotheses being tested is very large (e.g. Bonferroni's inequality). Recent approaches such as White's (2000) RC test, the SPA test developed by Hansen (2005) and the Step-SPA developed by Hsu et al. (2010) can circumvent this problem.

Reality Check test and Superior Predictive Ability test

Given m rules for some variable, let $p_{k,t}(k = 1,2, \ldots, m \text{ and } t = 1,2, \ldots n)$ denote their performance measures (relative to a benchmark) over time. Suppose that $E(p_{k,t}) = \mu_k$ for all t and for each k and that $p_{k,t}$ may be dependent across k. We test the following inequality constraints to determine whether a TTR can generate positive mean returns:

$$H_0: \mu^k \leq 0, k = 1, \ldots m \quad (2)$$

We define r_t to be the return on this asset at time t and $\delta_{\mathrm{k,t-1}}$ to be the trading signal generated by the k^{th} trading rule at time *t-1*. The latter takes the values of 1, 0, -1, corresponding to a long position, neutral position, and a short position, respectively. $R_{k,t} = \delta_{k,t-1} r_t$ is the realised return of the k^{th} trading rule, and (2) is the null hypothesis that no trading rule can generate a positive mean return. The $p_{k,t}$ will be dependent across rules as they are based on the same return, r_t. Following Hansen (2005), we impose the condition that $p_t = (p_{1,t}, \dots, p_{m,t})'$ exhibits weak dependence over time.[2] Under this condition the test statistic $\sqrt{n}(\bar{p} - \mu)$ obeys a central limit theorem and will converge in distribution to a normal distribution with mean 0 and variance $\boldsymbol{\Omega}$:

$$\sqrt{n}(\bar{p} - \mu) \xrightarrow{d} N(0, \Omega) \quad (3)$$

where $\bar{p} = n^{-1} \sum_{t=1}^{n} p_t$, $\mu = E(p_t)$, $\Omega \equiv \lim_{n \to \infty} var(n^{\frac{1}{2}}(\bar{p} - \mu))$.

The above assumption ensures the validity of the stationary bootstrapping procedure and the consistency of the Politis and Romano (1994) covariance matrix estimator. White's RC test is based on the following statistic:

$$RC = \max_{k=1,\dots,m} \sqrt{n}\bar{p}_k \quad (4)$$

where $\bar{p}_k$ is the k^{th} element of $\bar{p}$. This test, as Hansen (2005) pointed out, is conservative as its null distribution is obtained under the least favourable configuration ($\mu = 0$). This implies it will lose power when many insignificant rules are included in the same test. To solve this problem, Hansen (2005) proposed the SPA test that avoids the least favourable configuration by the re-centring the bootstrap distribution. This test statistic is given by the following:

$$SPA_n = \max_{k=1,\dots,m}(\sqrt{n}\overline{p_k}, 0) \quad (5)$$

Step-SPA test

Both the RC and SPA test can indicate only whether there is any rule in the tested sample that violates their respective null hypotheses but they cannot identify with precision all of the rules outperform a given benchmark This problem was resolved by Romano and Wolf (2005) who introduced a stepwise version of the White's RC test capable of identifying all significant rules. However, the shortcoming of this methodology is its conservativeness which it shared with White's RC procedure. The natural extension to this framework was proposed by Hsu et al. (2010) with the introduction of the Step-SPA which combines the Romano and Wolf stepwise procedure with the more powerful SPA test. This procedure

[2] ASSUMPTION: $\{p_t\}$ is strictly stationary and α-mixing of size $-(2+\varepsilon)(r+\varepsilon/(r-2)$, for some $r > 2$ and $\varepsilon > 0$, where $E|p_t|(r+\varepsilon) < 1$ with $|.|$ the Euclidean norm, and $var(p_{k,t}) > 0$ for all k.

applies the Politis and Romano (1994) stationary bootstrap using random blocks whose length is determined by the realization of a geometric distribution with parameter $Q \in [0,1)$. Repeating the procedure B times yields the following statistic:

$$\hat{q}^*_{\alpha_0} = \max\left(\hat{q}_{\alpha_0}, 0\right) \quad (6)$$

where $\hat{q}_{\alpha_0} = \inf\{q | P^*[\sqrt{n}\max_{k=1,..m}(\bar{p}^*_k - \bar{p}^* + \hat{\mu}_k) \leq q] \geq 1 - \alpha_0\}$ and $(1 - \alpha_0)$ re-centres the distribution of the test statistic and P^* is the bootstrapped probability measure. Having ranked the rules in descending order according to their Step-SPA *p*-value, one rejects each consecutive individual rule k if $\hat{\mu}^c_k > \tilde{q}_1(\alpha_0)$. If no rule is rejected, the test stops there. Otherwise, the significant rule is removed and the estimation is repeated by calculating a new test statistic $\tilde{q}_2(\alpha_0)$. This procedure iterates until no further rule is rejected.

3. Empirical Results

3.1 Summary Statistics

Table 1 reports the statistics for daily log exchange rate returns in US dollars (USD).

Table 1 Descriptive statistics for daily logged exchange rate returns

The table reports summary statistics for all 22 sample currencies. The exchange rate is defined as the US dollar price of one unit of foreign exchange. s_t is the logarithm of the spot daily exchange rate. $\rho(k)$ is the k^{th} order serial correlation of $(s_t - s_{t-1})$.

$s_t - s_{t-1}$	AUD	CAD	CZK	DKK	EUR	HKD	HUF	INR	ISL	JPY	LVL
Mean	-0.002%	-0.003%	-0.007%	0.000%	0.006%	0.000%	0.008%	0.013%	0.002%	0.000%	0.011%
SD	0.837%	0.571%	0.785%	0.631%	0.634%	0.029%	0.891%	0.735%	0.489%	0.696%	0.628%
Skewness	0.716	-0.075	0.049	-0.160	-0.135	-2.718	0.132	0.045	0.386	-0.460	0.048
Kurtosis	14.520	8.604	6.833	5.435	5.423	66.136	6.870	7.821	8.365	8.270	6.714
ρ(1)	-0.007	-0.004	0.000	-0.001	-0.001	0.000	0.003	0.003	0.006	-0.005	-0.005
ρ(2)	-0.003	-0.008	0.000	0.000	0.000	0.000	0.001	0.001	-0.006	-0.009	-0.009
ρ(3)	0.002	0.009	0.003	-0.001	-0.001	0.000	0.008	0.008	0.004	0.009	0.009
ρ(4)	0.000	0.000	-0.030	-0.023	-0.023	0.000	-0.060	-0.061	0.015	0.010	0.010
ρ(5)	0.000	0.000	-0.013	-0.008	-0.008	0.000	-0.030	-0.030	-0.003	-0.003	-0.003
ρ(6)	-0.014	-0.027	-0.025	-0.019	-0.019	0.000	-0.027	-0.027	-0.001	0.009	0.010

$s_t - s_{t-1}$	LTL	NZD	NOK	PHP	PLN	RUB	SGD	ZAR	SEK	CHF	GBP
Mean	0.009%	-0.002%	0.002%	0.006%	-0.002%	0.019%	-0.004%	0.021%	0.002%	-0.010%	0.001%
SD	0.637%	0.863%	0.768%	0.502%	0.817%	0.735%	0.386%	1.036%	0.762%	0.720%	0.574%
Skewness	0.059	0.378	0.005	-1.772	0.329	0.603	-0.403	0.300	-0.160	-0.788	0.234
Kurtosis	6.522	7.979	7.884	73.738	10.466	93.369	12.738	8.623	6.625	25.964	9.215
ρ(1)	-0.005	-0.007	-0.004	0.000	0.000	0.000	-0.001	-0.005	-0.001	0.003	0.000
ρ(2)	-0.009	0.001	-0.006	0.000	0.000	0.000	-0.001	0.002	0.000	-0.001	0.001
ρ(3)	0.009	-0.001	0.017	-0.001	-0.001	0.000	0.003	-0.004	0.005	-0.007	-0.008
ρ(4)	0.010	0.001	-0.029	0.001	0.001	0.001	0.000	-0.004	-0.006	0.028	-0.056
ρ(5)	-0.003	0.001	-0.012	0.004	0.004	0.003	0.000	0.002	-0.001	0.007	0.003
ρ(6)	0.010	-0.002	0.003	0.014	0.016	0.012	-0.004	0.007	-0.004	0.019	-0.008

The mean daily returns show that the dollar depreciates against all but seven of the currencies in our sample. Note that the mean return for pegged or managed currencies against the USD exhibits returns very close to zero. With the exception of the HKD (standard deviation of 0.029%), all FX returns display substantial daily volatility with standard deviations ranging from 0.386% to 1.036%. They all exhibit excess kurtosis and the majority have a positively skewed return distribution. All the Jarque-Bera statistics, not reported in this study, strongly reject the null hypothesis that returns are normally distributed.

Table 1 also reports the results for testing for autocorrelation at up to six lags to check whether there is any exploitable systematic pattern in the returns which in principle should be *iid* series. We use the novel Lobato et al. (2001) test that produces more robust results for dependent time series y_t, (such as GARCH processes) with mean m, that exhibit the properties of a martingale difference sequence. Here the bounds are equal to $\pm 1.96\sqrt{\left(\frac{\hat{\tau}^*_{jj}}{n}\right)}$, where $\hat{\tau}^*_{jj} = \frac{\left(\frac{i}{n}\right)\sum_{t=1}^{n-j}(y_t - m)^2(y_{t+j} - m)^2}{c(0)^2}$ and $c(0) = \frac{\sum_{t=1}^{n}(y_t - m)^2}{n}$ where n is the number of observations. There is no significant evidence of autocorrelation at any lag for all the sample currencies.

3.2 Trading rule profitability

Table 2 displays the number of significant TTRs for each category of trading rules allowing for interest rate differentials. It also gives the percentage of significant TTRs within each category of rules e.g. filter rules. All currencies are found to have large numbers of economically significant TTRs. Their proportions range from an average of 18.3% (20,676 rules) for the South African Rand to a massive 47.7% (53913 rules) for the Swiss franc. The overall median proportion of significant trading rules in Panel B is 35% while the overall average is slightly lower at 36.3%. The sheer numbers of significant TTRs is perhaps surprising given that the sample extends up till mid-2015 and the accepted wisdom is that there has been a decline in the number of significant rules in recent decades. There is more variation in the proportion of significant trading rules by category. They range from 0% of the RSI rules for the Japanese Yen (JPY) to 100% of trading rules for the MACD (zero) rule for the Indian Rupee (INR**)** and Russian rouble (RUB).

We averaged the proportion of significant trading rules by category across all currencies (Table 2, Panel B). The newer TTRs tend to exhibit a higher mean and median proportion of significant rules as compared with traditional rules. The mean proportions are 49% for RSI, 42% for Bollinger Band, 62% for MACD, and 55% and MACD(zero) rules. The three classes of MA rules tested have on average 34%-36% of significant rules. The categories with the lowest proportion of significant trading rules are the traditional Channel Breakout (CBR) and Trading Break Range (TBR) rules with 12% and 22%, respectively.

Table 2 Total number of profitable trading rules

Panel A in this table, reports the number and percentage of technical trading rules that generate positive mean annualised excess returns by currency after taking into consideration interest rate differentials. The overall universe of trading rules is 113,148. Panel B provides the mean and median of the number (and the percentage) of significant trading rules by type.

Panel A

		AUD		CAD		CZK		DKK		EUR		HKD		HUF		INR		ISL		JPY		LVL	
		N	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*	*N*	*(%)*
MA	*AMA*	5095	**25.92**	9189	**46.75**	4562	**23.21**	9211	**46.86**	9956	**50.65**	7081	**36.02**	4458	**22.68**	5976	**30.40**	6885	**35.03**	9482	**48.24**	9581	**48.74**
	EMA	5131	**26.10**	9204	**46.83**	4620	**23.50**	9066	**46.12**	9938	**50.56**	5825	**29.63**	3248	**16.52**	5976	**30.96**	6859	**34.90**	7932	**40.35**	9433	**47.99**
	TMA	5405	**27.50**	9365	**47.64**	4829	**24.57**	8779	**44.66**	9313	**47.38**	6664	**33.90**	4896	**24.91**	6724	**34.21**	6385	**32.48**	9824	**49.98**	9104	**46.32**
CBO		2500	**16.53**	2793	**18.47**	923	**6.10**	1358	**8.98**	1490	**9.85**	0	**0.00**	2709	**17.92**	813	**5.38**	3217	**21.28**	1466	**9.70**	1038	**6.87**
Filter		4898	**32.39**	9549	**63.15**	8069	**53.37**	8396	**55.53**	8879	**58.72**	4527	**29.94**	4598	**30.41**	4905	**32.44**	8306	**54.93**	10036	**66.38**	4686	**30.99**
TBR		682	**27.06**	690	**27.38**	247	**9.80**	342	**13.57**	419	**16.63**	0	**0.00**	634	**25.16**	135	**5.35**	926	**36.75**	432	**17.14**	382	**15.16**
BOLL		6793	**48.14**	6344	**44.95**	6431	**45.57**	5443	**38.57**	5641	**39.97**	3839	**27.20**	6794	**48.14**	6894	**48.85**	3003	**21.28**	6376	**45.18**	5162	**36.58**
RSI		1792	**26.67**	4164	**61.96**	2064	**30.71**	5792	**86.19**	3536	**52.62**	5144	**76.55**	5712	**85.00**	5748	**85.54**	4952	**73.69**	0	**0.00**	1624	**24.17**
MACD	*norm*	238	**80.95**	235	**79.93**	255	**86.73**	254	**86.39**	72	**24.49**	116	**39.46**	18	**6.12**	246	**83.67**	102	**34.69**	281	**95.58**	230	**78.23**
	Zero	209	**71.09**	127	**43.20**	42	**14.29**	74	**25.17**	145	**49.32**	289	**98.30**	273	**92.86**	294	**100.00**	114	**36.75**	30	**10.20**	204	**69.39**
Total		32743	**28.94**	51660	**45.66**	32042	**28.32**	48715	**43.05**	49389	**43.65**	33485	**29.59**	33340	**29.47**	37711	**33.33**	40749	**36.01**	45859	**40.53**	41444	**36.63**

		LTL		NZD		NOK		PHP		PLN		RUB		SGD		ZAR		SEK		CHF		GBP	
		N	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**	**N**	**(%)**
MA	*AMA*	9694	**49.32**	4253	**21.64**	5525	**28.11**	3993	**20.31**	11967	**60.88**	6117	**31.12**	8128	**41.35**	1443	**7.34**	6329	**32.20**	9070	**46.14**	10765	**54.77**
	EMA	9800	**49.86**	3877	**19.72**	5424	**27.59**	3255	**16.56**	11519	**58.60**	5900	**30.02**	7755	**39.45**	1093	**5.56**	6636	**33.76**	10011	**50.93**	10567	**53.76**
	TMA	9416	**47.90**	3678	**18.71**	5981	**30.43**	5269	**26.81**	11122	**56.58**	6875	**34.98**	7605	**38.69**	1635	**8.32**	6087	**30.97**	9930	**50.52**	11614	**59.09**
CBO		1686	**11.15**	1607	**10.63**	3217	**21.28**	1279	**8.46**	2835	**18.75**	1826	**12.08**	2090	**13.82**	900	**5.95**	2602	**17.21**	4241	**28.05**	3342	**22.10**
Filter		4650	**30.75**	4472	**29.58**	4662	**30.83**	4433	**29.32**	6187	**40.92**	5057	**33.45**	8811	**58.27**	4320	**28.57**	4173	**27.60**	9474	**62.66**	5127	**33.91**
TBR		538	**21.35**	450	**17.86**	936	**37.14**	297	**11.79**	731	**29.01**	908	**36.03**	580	**23.02**	237	**9.40**	740	**29.37**	1109	**44.01**	934	**37.06**
BOLL		5089	**36.06**	6636	**47.02**	7121	**50.46**	7727	**54.75**	6342	**44.94**	7899	**55.97**	4910	**34.79**	8528	**60.43**	6111	**43.30**	3815	**27.03**	4826	**34.20**
RSI		1948	**28.99**	2092	**31.13**	1232	**18.33**	6550	**97.47**	304	**4.52**	4852	**72.20**	4556	**67.80**	2091	**31.12**	1866	**27.77**	6068	**90.30**	744	**11.07**
MACD	*Norm*	241	**81.97**	227	**77.21**	213	**72.45**	274	**93.20**	256	**87.07**	76	**25.85**	90	**30.61**	226	**76.87**	34	**11.56**	69	**23.47**	249	**84.69**
	Zero	131	**44.56**	194	**65.99**	222	**75.51**	150	**51.02**	32	**10.88**	294	**100.00**	150	**51.02**	203	**69.05**	248	**84.35**	126	**42.86**	3	**1.02**
Total		43193	**38.17**	27486	**24.29**	34533	**30.52**	33227	**29.37**	51295	**45.33**	39804	**35.18**	44675	**39.48**	20676	**18.27**	34826	**30.78**	53913	**47.65**	48171	**42.57**

Panel B

	AMA	EMA	TMA	CBO	FILTER	TBR	BOLLINGER	RSI	MACD	MACD (zero)
MEAN	7,216	6,958	7,295	1,997	6,283	561	5,987	3,311	182	162
	37%	**35%**	**37%**	**13%**	**42%**	**22%**	**42%**	**49%**	**62%**	**55%**
MEDIAN	6983	6748	6800	1756	4981	559	6343	2814	229	150
	36%	**34%**	**35%**	**12%**	**33%**	**22%**	**45%**	**42%**	**78%**	**51%**

Among significant MA rules, TTRs based on the Triangular MA filter have the highest percentage for most currencies (11,) followed by Arithmetic MA (9) and Exponential MA (2) rules. Unreported results show that the best AMA rule achieved returns of 7.24% pa across currencies as compared with 7.18% for TMA and 6.81% for EMA rules. The best performing rules out of the CBO, TBR and filter rules are the filter rules for all but four currencies.

The best rules based on the newer technical indicators are clearly the most successful trading rules in our sample and Table 3 summarises their performance. In general, the Bollinger band rules stand out for their very high annualised returns with an overall mean of 20.6% across all currencies. Interestingly, the identity of the best rule is virtually the same across all currencies (*e*=5, *nstd*=1, *b*=0, *h*=0, *d*=0). The best performance for this set of rules is achieved for the South African Rand (ZAR) with 29.7%. excluding the special case of the HKD, all the remaining annualised returns are in excess of 10% and they exceed 20% for some 13 currencies. The RSI are the only other set of rules that, on average, generates annualised returns in excess of 10% (10.8%). By contrast, the best traditional TTRs generate average annualised returns in the 6-7% range, only. The latter are in line with extant findings in the literature like those of Cornell and Dietrich (1978), Dooley and Shafer (1983) and Qi and Wu (2006).

Table 3 Best technical indicator trading rules

This table reports the best Bollinger Band, MACD, MACD (zero) and RSI trading rules, their calibration parameters and annualised mean excess return that accounts for interest rate differentials. Explanation of the calibration parameters for each of the rules can be found in the appendix A2.

	Bollinger Bands						MACD				MACD(zero)				RSI					
	e	nstd	b	c	d	E(*R*)	b	c	d	E(*R*)	b	C	d	E(*R*)	e	uppb	lowb	c	d	E(*R*)
AUD	5	1	0	0	0	**24.11**	0.001	0	0	**4.78**	0.001	0	0	**4.78**	14	50	10	0	0	**13.84**
CAD	5	1	0	0	0	**16.61**	0.01	0	0	**1.31**	0.01	0	0	**1.31**	45	50	10	0	0	**6.62**
CZK	5	1	0.0005	0	0	**28.46**	0.05	0	0	**8.00**	0.05	0	0	**8.00**	14	50	40	0	0	**16.28**
DKK	5	1	0	0	0	**20.69**	0.01	0	0	**6.85**	0.01	0	0	**6.85**	25	50	10	0	0	**13.19**
EUR	5	1	0	0	0	**21.09**	0.001	0	0	**7.03**	0.001	0	0	**7.03**	25	50	10	0	0	**13.70**
HKD	5	1	0	0	0	**0.49**	0.01	4	0	**0.30**	0.01	4	0	**0.30**	14	70	10	0	0	**0.38**
HUF	5	1	0	0	0	**27.49**	0	1	1	**7.29**	0	1	1	**7.29**	14	50	10	1	0	**7.44**
INR	5	1	0	0	10	**17.32**	0	0	1	**11.31**	0	0	1	**8.46**	14	50	10	0	0	**8.56**
ISL	1	1	0	0	0	**17.18**	0	0	1	**8.86**	0	0	1	**5.23**	14	60	10	0	1	**11.77**
JPY	5	1	0	0	0	**21.63**	0.05	0	0	**4.77**	0.05	0	0	**4.77**	45	80	10	0	0	**-**
LVL	5	1	0	0	0	**19.44**	0.001	0	0	**6.46**	0.001	0	0	**6.46**	14	50	10	0	0	**12.87**
LTL	5	1	0	0	0	**19.64**	0.005	0	0	**8.04**	0.005	0	0	**8.04**	25	50	10	0	0	**12.73**
NZD	15	1	0	0	15	**24.77**	0	0	1	**12.93**	0	0	1	**4.46**	25	50	10	0	1	**14.17**
NOK	5	1	0	0	0	**23.41**	0.0005	0	0	**2.59**	0.0005	0	0	**2.59**	14	50	10	0	0	**11.09**
PHP	5	1	0	0	0	**15.66**	0	0	0	**6.51**	0	0	0	**6.51**	14	50	10	3	0	**4.64**
PLN	5	1	0	0	0	**27.81**	0.001	0	0	**9.01**	0.001	0	0	**9.01**	14	50	10	0	0	**18.13**
RUB	5	1	0	0	0	**24.37**	0.05	0	0	**13.37**	0.05	0	0	**13.37**	14	50	40	0	0	**17.54**
SGD	5	1	0	0	0	**10.86**	0.001	0	0	**4.41**	0.001	0	0	**4.41**	14	50	10	0	0	**8.02**
ZAR	5	1	0	0	0	**29.65**	0	0	1	**12.06**	0	0	1	**12.06**	20	50	20	0	0	**15.76**
SEK	5	1	0	0	0	**24.05**	0.001	0	0	**4.72**	0.001	0	0	**4.72**	25	50	20	0	0	**11.86**
CHF	5	1	0	0	0	**21.63**	0.05	5	0	**4.08**	0.05	5	0	**4.08**	20	50	10	0	0	**10.91**
GBP	5	1	0	0	0	**17.65**	0	0	0	**2.85**	0	0	0	**2.85**	14	50	10	0	0	**7.80**
Average						**20.64**				**6.71**				**6.03**						**10.79**

3.3 Subsample analysis

As a robustness check, we divided our sample period into two sub-samples, the first from 1997:10 to 2005:12 and the second from 2006:01 to 2015:06. As shown in Table 4 (Panel A), most currencies have a higher percentage of significant trading rules in the later sub-sample. In both sub-samples, the best performing TTRs for most currencies are those based on the new technical indicators and Panel B provides a summary of their performance for this set of rules. Note that, on average, the returns of the best performing trading rule in the later sub-sample is at a minimum 2 percentage points higher than those in the sub-sample with a maximum of approximately 3.5 percentage points for the Bollinger bands. Overall there is a tendency to find larger numbers of significant rules and more profitable rules in the later sub-sample which is contrary to the Lo (2004) adaptive markets hypothesis. This may be explained by the fact that later sub-sample mostly coincides with a period of significant market volatility over the years following the US sub-prime crisis.

Table 4 Sub-sample analysis

Panel A in this table, provides the mean of the number (and percentage) of significant trading rules by type for each sub-sample. Panel B reports the annualised mean excess return, accounting for interest rate differential for the best performance of the best Bollinger Band, MACD, MACD (zero) and RSI trading rules in the two subsamples. Sub-sample 1 runs from1997:10 to 2005:12 and sub-sample 2 from 2006:01 to 2015:06.

Panel A

	AMA	EMA	TMA	CBO	FILTER	TBR	BOLLINGER	RSI	MACD	MACD (zero)	TOTAL
Subsample1	8,305 42%	7,993 41%	8,660 44%	6,861 45%	2,667 18%	743 29%	4,078 29%	3,557 53%	159 54%	177 60%	43200 **38%**
Subsample2	8953 46%	8819 45%	9016 46%	5902 39%	2124 14%	617 24%	5567 39%	2404 36%	142 48%	196 67%	43628 **39%**

Panel B

	Bollinger Bands		**MACD**		**MACD(zero)**		**RSI**	
	1997-2005	**2006-2015**	**1997-2005**	**2006-2015**	**1997-2005**	**2006-2015**	**1997-2005**	**2006-2015**
AUD	22.48	25.27	12.72	13.75	4.45	8.26	12.97	14.81
CAD	13.17	19.67	5.01	7.66	2.11	1.11	6.15	8.65
CZK	27.20	29.89	14.42	15.40	5.15	10.39	12.40	19.16
DKK	21.75	19.97	8.75	12.47	6.13	8.39	13.19	13.53
EUR	22.97	19.65	8.90	12.72	6.33	7.39	13.77	13.53
HKD	0.34	0.71	0.46	0.39	0.26	0.40	0.28	0.51
HUF	22.02	32.19	9.87	15.15	7.99	7.20	8.31	9.13
INR	9.52	18.54	5.90	11.51	3.14	7.81	3.31	9.82
ISL	9.82	18.64	3.92	8.71	8.19	5.66	9.33	12.23
JPY	23.10	20.19	12.82	9.97	4.65	5.08	0.00	4.42
LVL	15.60	20.27	9.73	13.63	5.00	7.66	8.87	13.40
LTL	19.06	19.70	8.35	12.73	3.10	8.95	7.74	13.54
NZD	20.47	32.62	13.75	20.02	3.79	10.96	16.08	13.22
NOK	21.26	25.48	10.27	12.09	2.01	4.31	10.10	15.67
PHP	18.19	13.48	9.03	6.90	10.01	3.71	10.24	1.84
PLN	23.05	29.66	13.49	15.64	5.93	10.45	12.48	20.29
RUB	7.37	27.61	2.85	13.66	4.00	15.11	7.11	19.70
SGD	10.87	10.65	8.58	6.24	3.56	5.34	9.19	7.90
ZAR	27.06	31.48	18.05	12.31	13.87	13.11	20.45	16.19
SEK	23.47	24.33	10.65	7.72	5.55	4.05	12.38	12.89
CHF	22.20	21.09	9.42	12.62	3.65	4.83	11.95	10.21
GBP	17.27	17.86	8.87	11.23	1.19	5.15	6.68	9.00
Average	18.10	21.77	9.36	11.48	5.00	7.06	9.68	11.80

3.4 Controlling for data snooping

Thus far, the analysis of TTRs has been conducted ignoring data-snooping bias. We run the Step-SPA test to identify all (including the best performing) significant rules against the benchmark of no excess returns. Unreported Step-SPA test results indicate that traditional TTRs are robustly significant only in a few cases. These include MA and filter rules for a small number of Asian currencies such as the HKD and INR. Table 5 presents the data-snooping adjusted SPA *p*-value for the best trading rule out of the set of TTRs based on technical indicators and the numbers of significant rules identified by the Step-SPA procedures. The results show that, controlling for data snooping bias, three (the exception is the MACD(zero) rule) the newer TTRs are robustly significant for every sample currency. The Bollinger band and RSI indicator rules have the highest numbers of robust rules across all currencies with most SPA *p*-values equal (or close) to 0.

Table 5 Robust technical indicator rules

This table presents the robust results for newer TTRs under the mean excess return criterion that accounts for interest rate differentials. It gives the SPA p-value and number of robust TTRs identified by the Step-SPA procedure for each currency.

`	Bollinger Bands rules		MACD trading rule		MACD(zero) trading rule		RSI		
	SPA p-value	Step-SPA	SPA p-value	Step-SPA	SPA p-value	Step-SPA	SPA p-value	Step-SPA	Total per currency
AUD	0	**29**	0.00	**7**	0.22	**0**	0.00	**32**	68
CAD	0	**12**	0.00	**5**	0.79	**0**	0.01	**16**	33
CZK	0	**61**	0.00	**7**	0.01	**7**	0.00	**17**	92
DKK	0	**61**	0.00	**7**	0.01	**2**	0.00	**60**	130
EUR	0	**67**	0.00	**7**	0.01	**2**	0.00	**56**	132
HKD	0	**2**	0.00	**61**	0.02	**235**	0.00	**52**	350
HUF	0	**33**	0.00	**7**	0.05	**0**	0.02	**5712**	5752
INR	0	**1322**	0.00	**219**	0.00	**278**	0.00	**5659**	7478
ISL	0	**25**	0.00	**7**	0.00	**0**	0.00	**40**	72
JPY	0	**51**	0.00	**7**	0.08	**0**	1.00	**0**	58
LVL	0	**30**	0.00	**7**	0.04	**0**	0.00	**32**	69
LTL	0	**35**	0.00	**7**	0.01	**1**	0.00	**40**	83
NZD	0	**54**	0.00	**7**	0.00	**0**	0.00	**40**	101
NOK	0	**28**	0.00	**7**	0.62	**0**	0.00	**16**	51
PHP	0	**131**	0.00	**7**	0.00	**134**	0.11	**0**	272
PLN	0	**36**	0.00	**7**	0.05	**0**	0.00	**32**	75
RUB	0	**112**	0.01	**5**	0.01	**294**	0.00	**11**	422
SGD	0	**71**	0.00	**8**	0.00	**4**	0.00	**64**	147
ZAR	0	**186**	0.00	**181**	0.01	**180**	0.00	**1508**	2055
SEK	0	**33**	0.00	**6**	0.18	**0**	0.00	**26**	65
CHF	0	**47**	0.00	**7**	0.29	**0**	0.00	**36**	90
GBP	0	**33**	0.00	**7**	0.30	**0**	0.00	**24**	64
Average		**112**		**27**		**52**		**612**	**803**

The results for both Bollinger bands and the RSI indicator are particularly striking as they have produced relatively large numbers of robust rules across the majority of currencies. Excluding managed and pegged currencies, they on average have 54 and 31 robust rules, respectively. On average, some 9.1% of total RSI rules are robust across currencies as are some 0.8% of total Bollinger band rules. The huge numbers of robust RSI rules for both the HUF and INR stand out with 5712 and 5659, respectively. The fluctuations of these currencies against the US dollar are directly or indirectly managed by their central banks: our results suggest that TTRs can operate in a “controlled environment” and achieve economically modest but statistically robust returns.

The sub-sample results of our data-snooping exercise are interesting and provide an indication of trend performance over our study period.[3] In line with the AMH, the small numbers of robust classical trading rules decrease significantly from the earlier to the later sub-sample. Table 6 presents the results for the relatively large numbers of robustly significant rules based on the new technical indicators. In contrast to traditional rules, the overall average (across currencies) number of robust rules tends to increase increases for three of the four technical indicator TTRs from the earlier to the later subsample. Focusing on individual currencies, the number of robust RSI rules increases in the later sub-sample in almost all cases while the results for the Bollinger Band and MACD rules are evenly split between increases and decreases. Thus, while the results support the AMH tenet that more complicated TTRs remain profitable for longer periods, on balance they are contrary to the main AMH tenet as larger numbers of technical indicator rules are significant in the later as compared with the earlier sub-sample.

Table 6 Changes in robust technical indicator rules

This table presents the numbers of robust TTRs under the mean excess return criterion that accounts for interest rate differential for the 1997-2005 and 2006-2015 subsamples. It gives number of robust TTRs identified by the Step-SPA procedure for each currency.

	Bollinger Bands rules		**MACD trading rule**		**MACD(zero) trading rule**		**RSI**	
	1997-2005	**2006-2015**	**1997-2005**	**2006-2015**	**1997-2005**	**2006-2015**	**1997-2005**	**2006-2015**
AUD	23	13	6	6	0	0	8	20
CAD	7	7	0	0	0	0	4	0
CZK	36	32	7	7	0	3	3	12
DKK	27	26	6	7	0	1	20	36
EUR	30	28	0	7	0	0	16	40
HKD	0	2	48	0	0	55	0	24
HUF	22	15	2	7	0	0	4704	0
INR	3	1322	0	221	0	7	0	5634
ISL	6	23	42	252	276	114	4	24
JPY	17	22	7	6	0	0	0	476
LVL	4	24	0	7	0	0	0	28
LTL	3	27	0	7	0	1	0	32
NZD	35	20	7	0	0	0	12	48
NOK	13	13	6	6	0	0	4	8
PHP	105	35	0	7	139	0	693	0
PLN	9	21	4	7	0	0	0	16
RUB	6	80	0	5	0	27	2	10
SGD	16	33	7	6	0	4	20	60
ZAR	44	8	13	0	3	0	238	1
SEK	17	11	5	0	0	0	15	16
CHF	23	21	3	7	0	0	16	20
GBP	14	15	6	7	0	0	0	4
Average	**21**	**82**	**8**	**26**	**19**	**10**	**262**	**296**

[3] Please note that, as discussed in the data section, not all currencies have a full set of observations in the earlier sub-sample 1997-2005.

4. Conclusions

This paper analysed the performance of 113,148 technical trading rules using daily data from 1997 to 2015 for a cross-section of 22 currencies quoted in US dollars. In evaluating the performance of trading rules, it has accounted for interest rate differentials and also controlled for data-snooping bias using the Step-SPA test developed by Hsu et al. (2010). This test avoids some of the shortcomings of White's Reality Check test and is able to test for the robustness of all significant trading rules. Our findings suggest that, prior to controlling for data-snooping bias, quite large numbers of technical trading rules are significantly profitable and can achieve annualised returns up to 30%.

The Step-SPA test results show that the numbers of robustly significant trading rules decreases sharply. There is a big divergence in the performance of traditional trading rules and that of newer trading rules based on technical indicators. After controlling for data-snooping bias, virtually none of the traditional trading rules is significant with *p*-values very close to 1. These results are in line with those in the literature suggesting that the performance of traditional trading rules has decreased over the past two decades (LeBaron, 2002; Neely, Weller and Ulrich (2007)). They are also consistent with recent data-snooping free investigations of technical trading rules (Qi and Wu, 2006; Kuang et al., 2010).

However, the results provide strong evidence that technical indicator rules such as Bollinger bands, RSI and MACD remains robustly profitable. After accounting for interest rate differentials and data snooping, some trading rules remain robustly significant across all currencies and both subsamples. This applies particularly to the Bollinger Band and RSI indicator rules. One direction for future research would be to explore the performance of trading signals generated from a mixture of rules such as a combination of traditional and technical indicator rules.[4]

[4] We are grateful to an anonymous reviewer for this suggestion.

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Appendix A

Table A.1 Sample currencies, currency codes and data span

The name of each currency is given in the first column with its ISO currency code in the second column. The mean and standard deviation of the daily forward discount and excess returns are expressed in percentage terms. The sample span by currency is in the final two columns.

CURRENCY		Forward discount(f_t-s_t)		Excess returns (f_{t-1}-s_t)		Sample	
		Mean (%)	St.Dev (%)	Mean (%)	St.Dev (%)		
Australian dollar	AUD	-0.0083	0.0163	0.0031	0.8641	27/10/1997	30/06/2015
Canadian dollar	CAD	-0.0006	0.0262	0.0093	0.5857	27/10/1997	30/06/2015
Czech koruna	CZK	-0.0037	0.0204	0.0132	0.7754	27/10/1997	30/06/2015
Danish krone	DKK	0.0003	0.0152	0.0057	0.6306	27/10/1997	30/06/2015
Euro	EUR	0.0017	0.0176	0.0059	0.6389	1/01/1999	30/06/2015
Hong Kong dollar	HKD	0.0020	0.0053	0.0018	0.0296	27/10/1997	30/06/2015
Hungarian forint	HUF	-0.0216	0.0183	-0.0231	0.8565	27/10/1997	30/06/2015
Indian rupee	INR	-0.0147	0.0264	-0.0207	0.3249	27/10/1997	30/06/2015
Israeli shekel	ISL	-0.0019	0.0049	0.0120	0.5431	29/03/2004	30/06/2015
Japanese yen	JPY	0.0134	0.0152	0.0252	0.7157	27/10/1997	30/06/2015
Latvian lat	LVL	-0.0020	0.0110	-0.0010	0.6263	29/03/2004	30/06/2015
Lithuanian lita	LTL	0.0009	0.0072	0.0065	0.6450	29/03/2004	30/06/2015
New Zealand dollar	NZD	-0.0115	0.0179	-0.0049	0.8848	27/10/1997	30/06/2015
Norwegian krone	NOK	-0.0051	0.0243	0.0006	0.7570	27/10/1997	30/06/2015
Philippine peso	PHP	-0.0204	0.0457	-0.0267	0.5431	27/10/1997	30/06/2015
Polish zloty	PLN	-0.0111	0.0238	0.0040	0.9235	11/02/2002	30/06/2015
Russian rouble	RUB	-0.0063	0.0214	-0.0102	0.5156	29/03/2004	30/06/2015
Singapore dollar	SGD	0.0065	0.0093	0.0126	0.3834	27/10/1997	30/06/2015
South African rand	ZAR	-0.0312	0.0302	-0.0406	1.0559	27/10/1997	30/06/2015
Swedish krona	SEK	0.0013	0.0256	0.0047	0.7573	27/10/1997	30/06/2015
Swiss franc	CHF	0.0081	0.0211	0.0210	0.6777	27/10/1997	30/06/2015
UK pound	GBP	-0.0051	0.0342	-0.0067	0.5877	27/10/1997	30/06/2015

Table A.2. Technical trading rules parameters and subsample analysis

	Parameters	Description	Value
Moving Average	***m***	Short run moving average	1,2,5,10,15,20,25,50,100,150,200,250
	n	Long run moving average	2,5,10,15,20,25,50,100,150,200,250,300
	b	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05
	d	Number of days for the delay filter	0,…,5
	c	Number of months position is held irrespectively of all other trading signals	0,1,2,5,10,15,20
Channel Rule	***e***	Evaluation period	1,2,5,10,15,20,25,50,100,150,200
	b1	Band for buy signals	0.001; 0.005;0.05;0.1,0.2
	b2	Band for sell signals	10% - 90% of b1
	d	As previous	0,…,5
	c	As previous	0,1,2,5,10,15,20
Trading range break	***e***	Evaluation period	1,2,5,10,15,20,25,50,100,150,200
	b	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05
	d	Number of days for the delay filter	0,…,5
	c	Number of months position is held irrespectively of all other trading signals	0,1,2,5,10,15,20
Filter Rule	***e***	Evaluation period	1,2,5,10,15,20,25,50,100,150,200
	b1	Band for buy signals	0.0005; 0.001; 0.005; 0.01; 0.05;0.1
	b2	Band for sell signals	0.0005; 0.001; 0.005; 0.01; 0.05;0.1
	d	As previous	0,…,5
	c	As previous	0,1,2,5,10,15,20
Bollinger Bands	***e***	Evaluation period	1,2,5,10,15,20,25,50,100,150,200
	nstd	Number of st.dev	1,…,4
	b	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1
	d	As previous	0,…,5
	c	As previous	0,1,2,5,10,15,20
Relative Strength Index	***e***	Evaluation period	14,20,25,30,35…50
	Lower bound	Long run moving average	10,20,30,40
	Upper bound	Fixed band multiplicative value	50,60,70,80,90
	d	As previous	0,…,5
	c	As previous	0,1,2,5,10,15,20
MACD (cross zero or normal)	***b***	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1
	d	As previous	0,…,5
	c	As previous	0,1,2,5,10,15,20

Table A.3 Universe of trading rules

AMA	19,656
EMA	19,656
TMA	19,656
CBO	15,120
Filter	15,120
TBR	2,520
Bollinger	14,112
RSI	6,720
MACD	294
MACD	294
TOTAL	**113,148**

Highlights

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- Studies data snooping bias for 22 currencies 1996-2015
- Universe of 113,148 trading rules
- Technical indicator rules are robust
- Some support for adaptive markets hypothesis