



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, Hsu, & Kuan, 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 market 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.

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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 (Gehrig & Menkhoff, 2004; Lui & Mole, 1998; Menkhoff, 1997; Menkhoff & Taylor, 2007; Oberlechner, 2001; Taylor & Allen, 1992). Evidence supporting the profitability of technical trading rules (TTRs) in the FX markets dates from the late 1980s (LeBaron, 1999, 2002; Levich & Thomas, 1993; Neely, 1997; Sweeney, 1986). 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 (Neely & 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 & 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 (Kuang, Schroder, & Wang, 2010; LeBaron, 2002; Levich & Thomas, 1993; Qi & Wu, 2006) 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, Hsu, and Kuan (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 (2005a, 2005b) 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

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the EMH. It tests Lo's (2004) adaptive market hypothesis (AMH) which Neely and Weller (2012) adduce as the most plausible explanation of TTR profitability. Neely, 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 (Kuang et al., 2010; Qi & Wu, 2006).

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 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 et al., 2009) and with recent studies (Kuang et al., 2010; Qi & Wu, 2006). 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 Neely 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, Sarno, Schmeling, and Schrimpf (2012a, 2012b). Table A.1 in Appendix A 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, 2002). 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 band and a 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.

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:

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

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

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, & 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 recognised 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.

2.4.1. Reality check test and superior predictive ability test

Given m rules for some variable, let $p_{k,t}$ ($k = 1, 2, \dots, m$ and $t = 1, 2, \dots, n$) 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:

$$H_0 : \mu^k \leq 0, k = 1, \dots, m. \tag{2}$$

We define r_t to be the return on this asset at time t and $\delta_{k,t-1}$ 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 Ω :

$$\sqrt{n}(\bar{p} - \mu) \rightarrow^d N(0, \Omega) \tag{3}$$

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

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:

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

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 that 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 of the bootstrap distribution. This test statistic is given by the following:

$$SPA_n = \max_{k=1, \dots, m} (\sqrt{n \bar{p}_k}, 0). \tag{5}$$

2.4.2. Step-SPA test

Both the RC and SPA tests can indicate only whether there is any rule in the tested sample that violates their respective null hypotheses but they cannot identify with precision that 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 applies the Politis and Romano (1994) stationary bootstrap using random blocks whose length is determined by the realisation of a geometric distribution with parameter $Q \in [0, 1)$. Repeating the procedure B times yields the following statistic:

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

where $\hat{q}_{\alpha_0} = \inf\{q | P^*[\sqrt{n} \max_{k=1, \dots, m} (\bar{p}_k^* - \bar{p} + \hat{\mu}_k) \leq q] \geq 1 - \alpha_0\}$ 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 $\hat{\mu}_k^c > \hat{q}_1(\alpha_0)$. 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 $\hat{q}_2(\alpha_0)$. 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).

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, Nankervis, and Savin (2001) test that produces more robust results for dependent time series y_t , (such as GARCH processes) when m , that exhibit the properties of a martingale difference sequence. Here the bounds are equal to $\pm 1.96 \sqrt{\frac{\hat{\sigma}_{jj}^*}{n}}$, where $\hat{\sigma}_{jj}^* = \frac{(\frac{1}{n}) \sum_{t=1}^{n-j} (y_t - m)^2 (y_{t+j-m})^2}{c(0)^2}$ 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.

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 $|\cdot|$ the Euclidean norm, and $\text{var}(p_{k,t}) > 0$ for all k .

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 1 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
$\rho(1)$	−0.007	−0.004	0.000	−0.001	−0.001	0.000	0.003	0.003	0.006	−0.005	−0.005
$\rho(2)$	−0.003	−0.008	0.000	0.000	0.000	0.000	0.001	0.001	−0.006	−0.009	−0.009
$\rho(3)$	0.002	0.009	0.003	−0.001	−0.001	0.000	0.008	0.008	0.004	0.009	0.009
$\rho(4)$	0.000	0.000	−0.030	−0.023	−0.023	0.000	−0.060	−0.061	0.015	0.010	0.010
$\rho(5)$	0.000	0.000	−0.013	−0.008	−0.008	0.000	−0.030	−0.030	−0.003	−0.003	−0.003
$\rho(6)$	−0.014	−0.027	−0.025	−0.019	−0.019	0.000	−0.027	−0.027	−0.001	0.009	0.010

Table 1 (continued)

$s_t - s_{t-1}$	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
$\rho(1)$	−0.005	−0.007	−0.004	0.000	0.000	0.000	−0.001	−0.005	−0.001	0.003	0.000
$\rho(2)$	−0.009	0.001	−0.006	0.000	0.000	0.000	−0.001	0.002	0.000	−0.001	0.001
$\rho(3)$	0.009	−0.001	0.017	−0.001	−0.001	0.000	0.003	−0.004	0.005	−0.007	−0.008
$\rho(4)$	0.010	0.001	−0.029	0.001	0.001	0.001	0.000	−0.004	−0.006	0.028	−0.056
$\rho(5)$	−0.003	0.001	−0.012	0.004	0.004	0.003	0.000	0.002	−0.001	0.007	0.003
$\rho(6)$	0.010	−0.002	0.003	0.014	0.016	0.012	−0.004	0.007	−0.004	0.019	−0.008

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 113148. Panel B provides the mean and median of the number (and the percentage) of significant trading rules by type.

		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
Panel B																							
		AMA		EMA		TMA		CBO		Filter		TBR		Bollinger		RSI		MACD		MACD (zero)			
Mean		7216		6958		7295		1997		6283		561		5987		3311		182		162			
Median		37%		35%		37%		13%		42%		22%		42%		49%		62%		55%			
		6983		6748		6800		1756		4981		559		6343		2814		229		150			
		36%		34%		35%		12%		33%		22%		45%		42%		78%		51%			

Table 2 (continued)

		LTL		NZD		NOK		PHP		PLN		RUB		SGD		ZAR		SEK		CHF		GBP	
		N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)	N	(%)
MA	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	
	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	
	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	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	
	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	

Bold emphasis highlights the number of significant trading rules per currency/type of trading rules (corresponding number of rules is to the left under the N column).

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% (20676 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 number 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.

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 and the MACD are the only other set of rules that, on average, generates annualised returns in excess of 10% (10.8% and 10.55% respectively). 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).

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 market 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.

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

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 Appendix A2.

	Bollinger bands					MACD					MACD (zero)					RSI				
	<i>e</i>	<i>nstd</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>E(R)</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>E(R)</i>	<i>b</i>	<i>C</i>	<i>d</i>	<i>E(R)</i>	<i>e</i>	Uppb	Lowb	<i>c</i>	<i>d</i>	<i>E(R)</i>
AUD	5	1	0	0	0	24.11	0	0	0	12.12	0.001	0	0	4.78	14	50	10	0	0	13.84
CAD	5	1	0	0	0	16.61	0.001	0	0	6.33	0.01	0	0	1.31	45	50	10	0	0	6.62
CZK	5	1	0.0005	0	0	28.46	0.001	0	0	14.92	0.05	0	0	8.00	14	50	40	0	0	16.28
DKK	5	1	0	0	0	20.69	0.05	0	0	10.34	0.01	0	0	6.85	25	50	10	0	0	13.19
EUR	5	1	0	0	0	21.09	0.05	0	0	10.64	0.001	0	0	7.03	25	50	10	0	0	13.70
HKD	5	1	0	0	0	0.49	0.1	5	15	0.42	0.01	4	0	0.30	14	70	10	0	0	0.38
HUF	5	1	0	0	0	27.49	0.1	0	0	12.91	0	1	1	7.29	14	50	10	1	0	7.44
INR	5	1	0	0	10	17.32	0.001	0	0	11.31	0	0	1	8.46	14	50	10	0	0	8.56
ISL	1	1	0	0	0	17.18	0.01	0	0	8.86	0	0	1	5.23	14	60	10	0	1	11.77
JPY	5	1	0	0	0	21.63	0.01	0	0	11.30	0.05	0	0	4.77	45	80	10	0	0	-
LVL	5	1	0	0	0	19.44	0.05	0	0	13.07	0.001	0	0	6.46	14	50	10	0	0	12.87
LTL	5	1	0	0	0	19.64	0.1	0	0	11.65	0.005	0	0	8.04	25	50	10	0	0	12.73
NZD	15	1	0	0	15	24.77	0.01	0	0	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	0.05	0	0	7.12	0	0	0	6.51	14	50	10	3	0	4.64
PLN	5	1	0	0	0	27.81	0.001	0	0	13.96	0.001	0	0	9.01	14	50	10	0	0	18.13
RUB	5	1	0	0	0	24.37	0.005	0	0	12.15	0.05	0	0	13.37	14	50	40	0	0	17.54
SGD	5	1	0	0	0	10.86	0	0	0	7.43	0.001	0	0	4.41	14	50	10	0	0	8.02
ZAR	5	1	0	0	0	29.65	0.001	0	0	14.52	0	0	1	12.06	20	50	20	0	0	15.76
SEK	5	1	0	0	0	24.05	0.01	0	0	8.49	0.001	0	0	4.72	25	50	20	0	0	11.86
CHF	5	1	0	0	0	21.63	0	0	0	10.95	0.05	5	0	4.08	20	50	10	0	0	10.91
GBP	5	1	0	0	0	17.65	0.01	0	0	9.70	0	0	0	2.85	14	50	10	0	0	7.80
Average						20.64				10.55				6.03						10.79

Bold emphasis highlights the expected return of a particular rule. Parameters of the rule are highlighted to the left of the E(R) column.

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 from 1997:10 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	8305	7993	8660	6861	2667	743	4078	3557	159	177	43200
	42%	41%	44%	45%	18%	29%	29%	53%	54%	60%	38%
Subsample2	8953	8819	9016	5902	2124	617	5567	2404	142	196	43628
	46%	45%	46%	39%	14%	24%	39%	36%	48%	67%	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	18.55	3.14	12.87	5.90	7.81	3.31	9.82	
ISL	9.82	18.65	8.19	8.71	3.92	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	9.42	11.54	4.93	7.06	9.68	11.80	

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 number of significant rules identified by the Step-SPA procedures.

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 band rules		MACD trading rule		MACD (zero) trading rule		RSI		Total per currency
	SPA <i>p</i> -value	Step-SPA	SPA <i>p</i> -value	Step-SPA	SPA <i>p</i> -value	Step-SPA	SPA <i>p</i> -value	Step-SPA	
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	0.06	0	0.00	40	72
JPY	0	51	0.00	7	0.08	0	1.00	0	58
LVL	0	30	0.00	7	0.05	0	0.00	32	69
LTL	0	35	0.00	7	0.01	1	0.00	40	83
NZD	0	54	0.00	7	0.27	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

Bold emphasis highlights the number of rules that were found to be significant following the Step-SPA procedure. To the left in the number in bold is the *p*-value for that particular set of rules.

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 sub-samples. It gives number of robust TTRs identified by the Step-SPA procedure for each currency.

	Bollinger band 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	6	7	0	0	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	6	15	6	4	262	296

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.

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 number of robust classical trading rules decreases 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.

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 number 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 (2009)). They are also consistent with recent data snooping free investigations of technical trading rules (Kuang et al., 2010; Qi & Wu, 2006).

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 sub-samples. 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

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 We are grateful to an anonymous reviewer for this suggestion.

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 rule parameters and subsample analysis.

	Parameters	Description	Value
Moving average	<i>m</i>	Short run moving average	1, 2, 5, 10, 15, 20, 25, 50, 100, 150, 200, 250
	<i>n</i>	Long run moving average	2, 5, 10, 15, 20, 25, 50, 100, 150, 200, 250, 300
	<i>b</i>	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05
	<i>d</i>	Number of days for the delay filter	0,...,5
	<i>c</i>	Number of months position is held irrespectively of all other trading signals	0, 1, 2, 5, 10, 15, 20
Channel rule	<i>e</i>	Evaluation period	1, 2, 5, 10, 15, 20, 25, 50, 100, 150, 200
	<i>b1</i>	Band for buy signals	0.001; 0.005; 0.05; 0.1, 0.2
	<i>b2</i>	Band for sell signals	10% - 90% of <i>b1</i>
	<i>d</i>	As previous	0,...,5
	<i>c</i>	As previous	0, 1, 2, 5, 10, 15, 20
Trading range break	<i>e</i>	Evaluation period	1, 2, 5, 10, 15, 20, 25, 50, 100, 150, 200
	<i>b</i>	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05
	<i>d</i>	Number of days for the delay filter	0,...,5
	<i>c</i>	Number of months position is held irrespectively of all other trading signals	0, 1, 2, 5, 10, 15, 20
Filter rule	<i>e</i>	Evaluation period	1, 2, 5, 10, 15, 20, 25, 50, 100, 150, 200
	<i>b1</i>	Band for buy signals	0.0005; 0.001; 0.005; 0.01; 0.05; 0.1
	<i>b2</i>	Band for sell signals	0.0005; 0.001; 0.005; 0.01; 0.05; 0.1
	<i>d</i>	As previous	0,...,5
	<i>c</i>	As previous	0, 1, 2, 5, 10, 15, 20
Bollinger bands	<i>e</i>	Evaluation period	1, 2, 5, 10, 15, 20, 25, 50, 100, 150, 200
	<i>nstd</i>	Number of st. dev	1,...,4
	<i>b</i>	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1
	<i>d</i>	As previous	0,...,5
Relative strength index	<i>c</i>	As previous	0, 1, 2, 5, 10, 15, 20
	<i>e</i>	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
	<i>d</i>	As previous	0,...,5
MACD (cross zero or normal)	<i>c</i>	As previous	0, 1, 2, 5, 10, 15, 20
	<i>b</i>	Fixed band multiplicative value	0, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1
	<i>d</i>	As previous	0,...,5
	<i>c</i>	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	2520
Bollinger	14,112
RSI	6720
MACD	294
MACD	294
Total	113,148

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