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Technical trading rule profitability in currencies: It's all about momentum

Mark C. Hutchinson [a,b], Panagiotis E. Kyziropoulos [a], John O'Brien [a,*], Philip O'Reilly [a,c], Tripti Sharma [d]

[a] University College Cork, Ireland
[b] Abu Dhabi University, the United Arab Emirates
[c] University of New South Wales, Australia
[d] Queen's Management School,Queen's University Belfast, the United Kingdom of Great Britain and Northern Ireland

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ABSTRACT

Recent academic and practitioner attention has focused on currency momentum. In this paper we replicate technical trading rules to assess their relationship with momentum. We find the effectiveness of technical trading rules falls significantly over time, with the mean Sharpe Ratio of our sample of portfolios falling from 0.66 in our in-sample period to 0.06 out-of-sample. Further, the returns do not survive modest transaction costs out-of-sample. We identify time series momentum as the single common factor driving returns across the range of strategies. Any abnormal return generated by technical trading rules is fully explained by time series momentum.

1. Introduction

Recent influential studies concluding that currency returns have a high degree of predictability based on both cross sectional and time series momentum (Menkhoff et al., 2012b; Moskowitz et al., 2012) have reinvigorated interest in the study of currency return predictability.

In this paper we re-investigate a set of technical trading rules, an investment approach widely used by professional traders (Menkhoff and Taylor, 2007). We test the rules on both a basket of liquid (G11) currencies and a broad sample of global currencies over a sample period ending April 2020. These currencies provide a natural environment to conduct a replication and out-of-sample study of technical trading rules, given the well documented recent evidence on momentum strategies.[1] Using portfolio analyses and time series tests, we find no evidence of continued technical trading rule profitability and demonstrate that time series momentum, the strategy of buying recent winners and selling recent losers (Moskowitz et al., 2012), fully accounts for the historic returns generated by these rules.

Technical trading strategies focus on past price series, analysing each currency in isolation. They extract investment information by a range of methods including; setting filters, comparing the moving averages over different time horizons, identifying trading channels and observing resistance and support levels (see, Menkhoff and Taylor, 2007; Qi and Wu, 2006). Technical trading rules such as the

* Correspondence to: O'Rahilly Building, University College Cork, College Road, Cork T12 K8AF, Ireland.
E-mail address: j.obrien@ucc.ie (J. O'Brien).

[1] Participants in these FX markets are generally professional investors and in recent years the move to algorithmic trade execution has driven down transaction costs and improved market efficiency (Barroso and Santa-Clara, 2015).

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moving average rule and filter rule have been shown to generate high portfolio performance (Neely et al., 1997). Existing studies of currency markets document positive but declining foreign exchange technical trading rule profitability out-of-sample (see, Neely et al., 2009; Olson, 2004; Qi and Wu, 2006).

We go beyond these existing studies by providing a unified portfolio analysis of the FX technical trading rule universe with consistent methodology. We carefully consider the robustness of our findings to different specifications of each of the technical trading rules and provide an explanation for the abnormal returns reported in the literature.

We make three key contributions, demonstrating that (1) there has been a significant fall in the effectiveness of technical trading rules, (2) returns do not survive transaction costs in recent periods, and (3) the abnormal returns identified in prior studies can be fully explained by a single common factor, time series momentum.

Four classes of technical trading rule are specified: Filter, Moving Average, Channel Breakout and Trading Range Breakout. For robustness, we consider a range of parameterisations, generating 388 rule-based portfolios. In addition, we examine a core version of each rule. Our analysis splits data into an in-sample period from January 1980 to December 1998, consistent with the Qi and Wu (2006) study of the four classes of technical trading rules, and an out-of-sample period, based on subsequent currency data from January 1999 to April 2020.

Our analysis shows that, in-sample, the core version of each rule generates a statistically significant positive result, with Sharpe ratios ranging from 0.60 (channel breakout) to 0.99 (filter rule). Out-of-sample, none of the core technical trading rules generates statistically significant investment returns.

Using the broader sample of portfolios, we confirm the drop in performance. The average Sharpe ratio of the 388 strategy portfolios is 0.62 in the in-sample period but this falls to 0.06 when measured out-of-sample. Following the application of modest transaction costs (decreasing over time), excess returns are either negative or not significantly different from zero.

To explain the source of technical trading rule returns in the in-sample period we document the relationship between the return series and time series momentum, using both principal component analysis and time series analysis. Using this combined approach, we confirm a strong and positive relationship between technical trading rule and time series momentum returns. We then demonstrate that the return of time series momentum accounts fully for any abnormal return of technical trading rules. Finally, we confirm these results hold across a broader basket of global currencies.

In summary, the key insights of our paper are that the well documented ability of technical trading rules to predict currency returns has completely disappeared for G11 currencies and that technical trading rules in currency markets are fully explained by time series momentum.

The remainder of this paper proceeds as follows. Section 2 provides a summary of related literature. Section 3 details our data. The different classes of technical trading rules and the portfolio analyses are described in Section 4. Section 5 provides analyses showing the link between technical trading rules and momentum. We conclude in Section 6.

2. Related literature

There have been recent advances in understanding of the factors that drive currency returns. This research has focused primarily on carry, momentum, and value as predictors. More broadly the capital markets literature has shown the importance of momentum across asset classes. Within this broader literature there is some limited evidence showing a link between technical trading rules and momentum.

Studies showing the high returns to carry include Brunnermeier et al. (2008), Burnside et al. (2011a, 2011b), Menkhoff et al. (2012a). Both cross sectional and time series momentum have been documented in currencies (see, Menkhoff et al., 2012b, Lustig et al., 2014; Zhang, 2022) while studies of value include Asness et al. (2013) and Menkhoff et al. (2017). More recently Hutchinson et al. (2022) examine all three in a unified analysis, demonstrating that returns have dissipated over time.

Beyond currency markets, time series momentum has been shown to be a powerful predictor of returns. These returns cannot be accounted for by risk-based explanations (see Moskowitz et al., 2012, Asness et al., 2013, He and Li, 2015, Kim et al., 2016, Georgopoulou and Wang, 2017, Lim et al., 2018, Hutchinson and O'Brien, 2020, Liu et al., 2021). Researchers have also documented time series momentum in higher frequency data (see, Shen et al., 2021 for bitcoin and Li et al., 2021 for broader asset classes).

The literature on the relationship between time series momentum and technical trading rules is limited to Hong and Satchell (2015) and Marshall et al. (2017) who show a theoretical and empirical link for equities. Ours is the first study demonstrating that momentum accounts for the returns of the technical trading rules in currency markets. This evidence is particularly timely as Ivanova et al. (2021) argue that the ongoing returns to technical trading rules in currencies are challenging for risk-based explanations.

Recent literature examines the high returns reported for academic predictors and the post-publication decline in performance. The three main theoretical explanations proposed are statistical bias, mispricing and rational expectations (McLean and Pontiff, 2016).

Statistical biases include the combination of unreported tests, lack of adjustment for multiple tests, direct and indirect p-hacking (Harvey, 2017). Given evidence on technical trading rules has been reported in the literature since the 1960 s (see, for example, (Poole, 1967)) statistical bias can be discounted as explaining the high returns to technical trading rules in currencies.

In the case of rational expectations, predictability reflects risk and should persist even when widely documented (Cochrane, 1999). If return predictability reflects rational expectations, then the availability of information on the predictor will not induce other investors to behave differently and the returns associated with a predictor should continue.

In contrast, if currency predictability is due to mispricing then returns should diminish after the underlying academic research has been widely disseminated (McLean and Pontiff, 2016). The extent of the decline is also dependent upon the intensity of academic attention, in terms of number of publications (Shanaev and Ghimire, 2021). Anomalies in equity markets have declined post

Table 1
Descriptive Statistics This table reports mean annual return and annualised volatility (standard deviation) of excess return of each currency against the US dollar. G11currency (Panel A) series run from January 1979 to April 2020. The global currency (Panel B) time series generally begin in January 1998 except BGN (March 2001), EGP (April 2001), ISK (August 1998), INR (February 1999), ILS (December 1999), RUB (September 2000), KRW (August 2004), THB (February 2005) and UAH (May 2010). All global currency series end in April 2020. All series are at daily frequency. The German Mark (DEM) is used in place of the Euro prior to 1999.

Country (Currency)	Mean Return (%)	Volatility (%)	Country (Currency)	Mean Return (%)	Volatility (%)
Panel A: G11 currencies					
Australia (AUD)	1.58	11.15	New Zealand (NZD)	2.65	12.17
Canada (CAD)	0.45	7.13	Norway (NOK)	0.01	10.75
Denmark (DKK)	0.09	10.51	Sweden (SEK)	-0.65	10.92
Euro Area (EUR)	-0.32	10.69	Switzerland (CHF)	-0.25	11.61
Japan (JPY)	-0.33	11.20	UK (GBP)	0.76	10.17
Panel B: Global currencies					
Brazil (BRL)	4.99	19.45	Malaysia (MYR)	1.19	10.40
Bulgaria (BGN)	1.69	9.90	Mexico (MXN)	1.88	10.84
Croatia (HRK)	2.17	10.01	Philippines (PHP)	2.32	7.01
Czech Republic (CZK)	2.58	12.04	Poland (PLN)	3.97	13.11
Egypt (EGP)	2.65	14.03	Russia (RUB)	1.59	13.52
Hong Kong (HKD)	-0.19	0.55	South Africa (ZAR)	1.27	16.39
Hungary (HUF)	3.23	13.17	South Korea (KRW)	1.52	11.34
Iceland (ISK)	2.99	13.26	Saudi Arabia (SAR)	0.34	0.36
India (INR)	2.67	7.09	Singapore (SGD)	0.17	5.86
Indonesia (IDR)	6.38	22.25	Taiwan (TWD)	-0.04	5.10
Israel (ILS)	2.50	7.77	Thailand (THB)	2.22	6.01
Kuwait (KD)	0.53	2.06	Ukraine (UAH)	2.36	18.11

publication (McLean and Pontiff, 2016) with the exception of some international markets with high arbitrage frictions (Jacobs and Müller, 2020; Zaremba et al., 2020). As currencies are highly liquid, feature no short selling constraints, and have low transaction costs, arbitrage can fully eliminate mispricing.

Recently documented evidence on the cross-section of currency market predictors is consistent with mispricing (Bartram et al., 2022). Our out-of-sample evidence, showing the returns to technical trading rules have disappeared, is also consistent with investors learning and responding to information to correct mispricing.

3. Data

This study focuses on the ten most liquid currencies against the US Dollar (G11 currencies) in addition to a sample of global currencies. Spot exchange rates are sourced from MSCI, and all rates are at daily frequency. The ICE Benchmark Administration (IBA) one-month LIBOR, or its equivalent, is used as the risk-free rate.

We derive a daily excess return series from the spot and risk-free rates, defined as:

$$r_{i,t} = \left(\frac{S_{i,t}}{S_{i,\quad t-1}}\right)\left(\frac{1+\quad r^{i}_{t-1}}{1+\quad r^{f}_{t-1}}\right)^{1/262} - 1 \tag{1}$$

$S_{i,t}$ is US dollar (USD) price of one unit of currency i at time t. The risk-free rates for the US dollar and currency i are r^f_{t-1} and r^i_{t-1} respectively, both at time $t-1$. The excess return, $r_{i,t}$, is the return to an investor who holds a long position in currency i for period $t-1$ to t, funded by borrowing at the US interest rate (r^f) and then converting the proceeds back to dollars at the closing spot price at the end of the period (Menkhoff et al., 2017). This is equal to the profit generated by holding a long position in a forward (or future) contract for period t.

We analyse the strategies' excess return series over a sample period beginning on 1st January 1980 and running to 30th April 2020. We use data from up to twelve months prior to this to construct the initial trading signals.

Descriptive statistics are reported in Panel A of Table 1 for G11 currencies. Average excess returns vary from 2.65 % for the New Zealand Dollar to − 0.65 % for the Swedish Krona. The volatilities of the majority of currencies lie in a narrow band from 10.17 % (UK Pound) to 12.17 % (New Zealand Dollar). The Canadian Dollar is the outlier with a volatility of 7.13 %.

Unsurprisingly, in Panel B of Table 1, global currencies' variation in returns and volatility is generally larger. Average returns vary from –0.04 % (Taiwan dollar) to 4.99 % for the Brazilian Real.

4. Technical trading rule portfolio analyses

We formulate our trading rules based on a recent comprehensive review of technical trading rules (Qi and Wu, 2006). The rules analysed are Filter Rule, Moving Average, Channel Breakout and Trading Range Breakout. Each rule generates a buy or sell trade signal to initiate a trade. Positions are held for a fixed holding period and then closed. We specify a consistent set of holding periods, $h \in \{1, 5, 10, 25\}$ days, across all strategies. The rules are implemented using daily price series.

4.1. Filter (FR)

This rule buys currency i if its daily closing spot price is a fixed proportion (x) above the low over the formation period. A sell signal is generated when the closing price drops by at least x from a trailing high. The change in price is defined in log terms.

$$FR_{i,t} = \left\{ \begin{array}{ll} +1, & if \log\left(\frac{S_{i,\quad t}}{Low_{i,t-1,k}}\right) \geq x \\ -1, & if \log\left(\frac{High_{i,t-1,k}}{S_{i,\quad t}}\right) \geq x \\ 0, & otherwise \end{array} \right\} \tag{2}$$

where $High_{i,t,k}$ and $Low_{i,t,k}$ are high and low prices over k most recent days. The formation period $k \in \{1, 2, 5, 10, 20, 25, 50\}$ and $x \in \{0.001, 0.005, 0.010\}$. This gives a total of eighty-four portfolios.

4.2. Moving average (MA)

This rule compares moving averages of the currency price over two different time horizons, generating a buy (sell) signal when the short term moving average crosses above (below) the long term moving average by a fixed amount. A moving average is defined as:

$$MA_{i,t,k} = \frac{1}{k}\sum_{i=1}^{k} S_{i,t-k+1} \tag{3}$$

$MA_{i,t,k}$ is the moving average of currency i at time t over a formation period k. The signal for a currency i at time t is defined as

$$MA_{i,t} = \left\{ \begin{array}{ll} +1, & if \quad MA_{i,t,ks} > (1+b) \quad MA_{i,t,kl} \\ -1, & if \quad MA_{i,t,ks} < (1-b) \quad MA_{i,t,kl} \\ 0, & otherwise \end{array} \right\} \tag{4}$$

The short and long moving average horizons are ks and kl respectively. Following (Brock et al., 1992; Neely et al., 2009; Qi and Wu, 2006) $ks \in \{1, 2, 5\}$ days and $kl \in \{20, 50, 150, 200\}$ days. The band, b, sets the amount by which the short-term moving average must move above (or below) the long-term average to generate a trade signal. This prevents whipsawing by reducing the number of trades in sideways markets (Brock et al., 1992). The band takes the values $b \in \{0, 0.005, 0.010\}$. There are 144 portfolios made up of combinations of the four parameters.

4.3. Channel breakout (CB)

Currency i is defined as trading in a channel when the high price over the previous k days is within a fixed proportion (x) of the low price over the same period. Once a channel has been identified, a buy (sell) signal is generated when the closing spot rate is above (below) the channel by a fixed proportion. The channel breakout signal of currency i at time t is defined as:

$$CB_{i,t} = \left\{ \begin{array}{ll} +1, & if \quad S_{i,t} > (1+b) \quad High_{i,t-1,k} \\ -1, & if \quad S_{i,t} < (1-b) \quad Low_{i,t-1,k} \\ 0, & otherwise \end{array} \right\} \Big| \frac{(High_{i,t-1,k} - Low_{i,t-1,k})}{Low_{i,t-1,k}} \leq x \tag{5}$$

where b represents the band around the low and high prices for currency i at t. The channel is defined over a look back period of k days, where $k \in \{5, 10, 15, 20, 25, 50, 100, 200\}$ days. The parameters are $x \in \{0.005, 0.010, 0.100\}$ and $b \in \{0, 0.005, 0.010\}$, subject to the constraint $b < x$. This results in sixty-four portfolios.[2]

4.4. Trading range breakout (TR)

The trading range is defined by the trailing k-day high and low prices. A buy (sell) signal is generated when the price moves above (below) the high (low) price of the trading range by a pre-set amount, the band. The trading signal for this rule for currency i at time t is:

$$TR_{i,t} = \left\{ \begin{array}{ll} +1, & if \quad S_{i,t} > (1+b)High_{i,t-1,k} \\ -1, & if \quad S_{i,t} < (1-b)Low_{i,t-1,k} \\ 0, & otherwise \end{array} \right\} \tag{6}$$

where b is the band around the top and bottom of the range. The values of the band, b, and lookback period, k, are consistent with Section 4.3. There are ninety-six different combinations of parameters and portfolios for this strategy.

[2] The trading channel disappears for lookback periods greater than or equal to 20 and 50 days for $x = 0.005$ and $x = 0.010$, respectively, in the out-of-sample period and therefore there are no new trading positions created.

4.5. Portfolio specification

The trade signal can take one of three values 1 (Buy), 0 (No Action), − 1 (Sell). We use an equal trade size across all currencies at any given time, consistent with Menkhoff et al. (2012). The size of the transaction (w_t) and consequently the position in the portfolio is:

$$w_t = \frac{1}{N_t} \tag{7}$$

N_t is the number of active currencies at t. This scheme produces a portfolio where, when a position is held in all currencies, the sum of the absolute values is equal to the capital invested. The gross excess return of a portfolio in any period is the sum of the excess return of the individual currencies ($r_{i,t}$) multiplied by the corresponding portfolio weight ($w_{i,t}$).

$$r_{s,t} = \sum_{i=1}^{N_t} w_{i,t}.r_{i,t} \tag{8}$$

Where $r_{s,t}$ is the return of strategy s at time t.

4.6. Transaction costs

The net return is derived by subtracting transaction costs from the gross return. These are defined by the transaction cost function of Hurst et al. (2017). This function is time dependent, decreasing over time, and measures cost as a proportion of one-way transaction value. The transaction cost is defined as 0.18 % up to 1992, 0.06 % from 1993 to 2002 and 0.03 % thereafter (Hurst et al., 2017). The net return, $r_{s,t}^{net}$, is the net excess return of strategy s and tc_t is transaction cost rate, both at time t.

$$r_{s,t}^{net} = r_{s,t} - tc_t \sum_{i=1}^{N_t} \left| w_{i,t} - w_{i,t-1} \right| \tag{9}$$

4.7. Portfolio performance measures

We use three performance metrics to assess technical trading rule portfolios: mean excess return, mean risk-adjusted return and Sharpe ratio. The risk-adjusted returns are the annualised intercept parameters of the Fama-French five-factor model (Fama and French, 1993), which combines equity and interest rate risk factors.

$$R_{s,t} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 TERM_t + \beta_5 DEF_t + \varepsilon_t \tag{10}$$

$R_{s,t}$ is the portfolio return to trading strategy s at time t. $RMRF_t$, SMB_t and HML_t are the market, size and value factors for the US stock market respectively, sourced from Kenneth French's data library. The term factor, $TERM_t$, is the difference in return between long- and short-term US government bonds. DEF_t is the credit default factor, the difference between the return of a portfolio of corporate bonds and a portfolio of long-term government bonds.[3]

To analyse whether technical trading rules in currency markets have economic relevance in the out-of-sample period, we first construct a core version of each strategy and then 388 portfolios made up of alternative specifications. We divide our sample period based on Qi and Wu (2006). The in-sample period is January 1980 to December 1998 and the out-of-sample period runs from January 1999 to April 2020.

4.8. Core strategy performance

We define our core strategy for each rule following the criterion set down by both Brock et al. (1992) and Qi and Wu (2006) which focuses on the portfolios that are most profitable in-sample. We identify these portfolios in terms of the highest Sharpe ratio net of transaction costs.

Each core technical trading strategy has a holding period of 25 days. The FR portfolio has a ten-day formation period and filter of 1 %. The MA core portfolio uses a one-day short MA, 200-days long MA and band of 0.5 %. The CB portfolio has a band of 1 %, a formation period of 100 days and maximum band width of 10 %. The TR core rule is a 100-day formation period and no bands. The key performance statistics are presented in Table 2.

Panel A reports full sample performance of core trading strategies. Pre-transaction costs, all trading strategies generate positive annualised portfolio average excess returns and are highly statistically significant. The mean return ranges between 0.52 % and 2.95 % per annum. The Sharpe ratio ranges from 0.32 to 0.53, for CB and TR, respectively. Annualised risk-adjusted alphas exhibit similar patterns.

The in-sample performance across trading styles, Table 2, Panel B, is consistent with the full sample results and prior literature. As expected, the annualised means, Sharpe ratios and alphas observed for the in-sample period are better than those reported in Panel A.

[3] The US Benchmark 10-Year Government Total Return Index and ICE Bank of America 10–15 Year US Corporate Total Return Index (from the Federal Reserve Economic Data website) are used as proxies for long-term government bond and corporate bond returns respectively,

Table 2

Performance of core strategies This table reports the performance with (Net performance) and without (Gross performance) transaction costs, of the core strategy for each trading rule. Performance is reported for three sample periods – full (Panel A), in-sample (Panel B) and out-of-sample (Panel C). Each technical trading strategy has a holding period of 25 days. The Filter Rule portfolio has a ten-day formation period and filter of 1 %, ($k = 10, x = 0.01$). The Moving Average Rule uses a one-day short MA, 200-days long MA and band of 0.5 %, $ks = 1, kl = 200$ $and b = 0.005$). The Channel Breakout Rule has a band of 1 %, a formation period of 100 days and maximum band width of 10 % ($b = 0.01, k = 100$ and $x = 10\%$). Trading Range Breakout Rule uses a 100-day formation period and no bands ($k = 200$ $and b = 0$). We report the mean annual return (Mean) and annualised volatility (Volatility) of excess returns. The Sharpe ratio is Mean/Volatility. Alpha is the annualised intercept of the multivariate Fama and French (1993) five-factor model and R^2 is the adjusted r-square of the model. *T*-statistics (in parentheses) for Mean and Alpha are based on Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors. *T*-statistics for the Sharpe ratio are calculated following Lo (2002). The symbols ***, **, and * denote statistical significance of parameter estimates at 1 %, 5 % and 10 % level of significance, respectively.

	Gross performance				Net performance			
	Filter	Moving Average	Channel Breakout	Trading Rng. Breakout	Filter	Moving Average	Channel Breakout	Trading Rng. Breakout
Panel A: Full sample								
Mean	2.27 ***	2.95 ***	0.52 **	2.57 ***	1.27 *	2.60 ***	0.37	1.85 ***
	(3.19)	(3.00)	(2.20)	(3.80)	(1.86)	(2.64)	(1.60)	(2.84)
Volatility	4.82	6.40	1.63	4.88	4.82	6.41	1.62	4.86
Sharpe ratio	0.47 ***	0.46 ***	0.32 **	0.53 ***	0.26 *	0.41 **	0.23	0.38 **
	(2.95)	(2.88)	(2.02)	(3.28)	(1.67)	(2.54)	(1.45)	(2.39)
Alpha	1.97 ***	3.56 ***	0.64 **	2.98 ***	0.96	3.20 ***	0.48 **	2.26 ***
	(2.61)	(3.36)	(2.58)	(3.94)	(1.33)	(3.02)	(2.00)	(3.07)
R^2	0.17	2.03	3.64	1.89	0.20	1.97	3.61	1.86
Panel B: In-sample								
Mean	4.85 ***	5.00 ***	0.94 ***	4.10 ***	3.16 ***	4.44 ***	0.68 **	2.90 ***
	(5.36)	(3.46)	(3.19)	(4.30)	(3.54)	(3.04)	(2.43)	(3.15)
Volatility	4.90	6.63	1.56	4.92	4.94	6.65	1.54	4.89
Sharpe ratio	0.99 ***	0.75 ***	0.60 **	0.83 ***	0.64 ***	0.67 ***	0.45 *	0.59 **
	(4.14)	(3.18)	(2.59)	(3.52)	(2.73)	(2.83)	(1.93)	(2.53)
Alpha	5.09 ***	5.43 ***	1.04 ***	4.69 ***	3.33 ***	4.82 ***	0.77 **	3.46 ***
	(4.95)	(3.40)	(2.92)	(4.36)	(3.27)	(2.99)	(2.25)	(3.32)
R^2	0.62	-0.65	1.33	1.08	0.55	-0.75	1.11	1.04
Panel C: Out-of-sample								
Mean	0.02	1.16	0.15	1.22	-0.38	0.99	0.09	0.92
	(0.02)	(0.88)	(0.42)	(1.26)	(-0.38)	(0.75)	(0.25)	(0.96)
Volatility	4.66	6.16	1.69	4.82	4.67	6.17	1.69	4.82
Sharpe ratio	0.01	0.19	0.09	0.25	-0.08	0.16	0.05	0.19
	(0.02)	(0.86)	(0.41)	(1.16)	(-0.38)	(0.74)	(0.25)	(0.88)
Alpha	-0.43	1.88	0.40	1.90 *	-0.84	1.71	0.33	1.61
	(-0.44)	(1.28)	(1.08)	(1.65)	(-0.85)	(1.16)	(0.91)	(1.40)
R^2	3.78	3.97	11.57	4.77	3.78	3.97	11.38	4.72

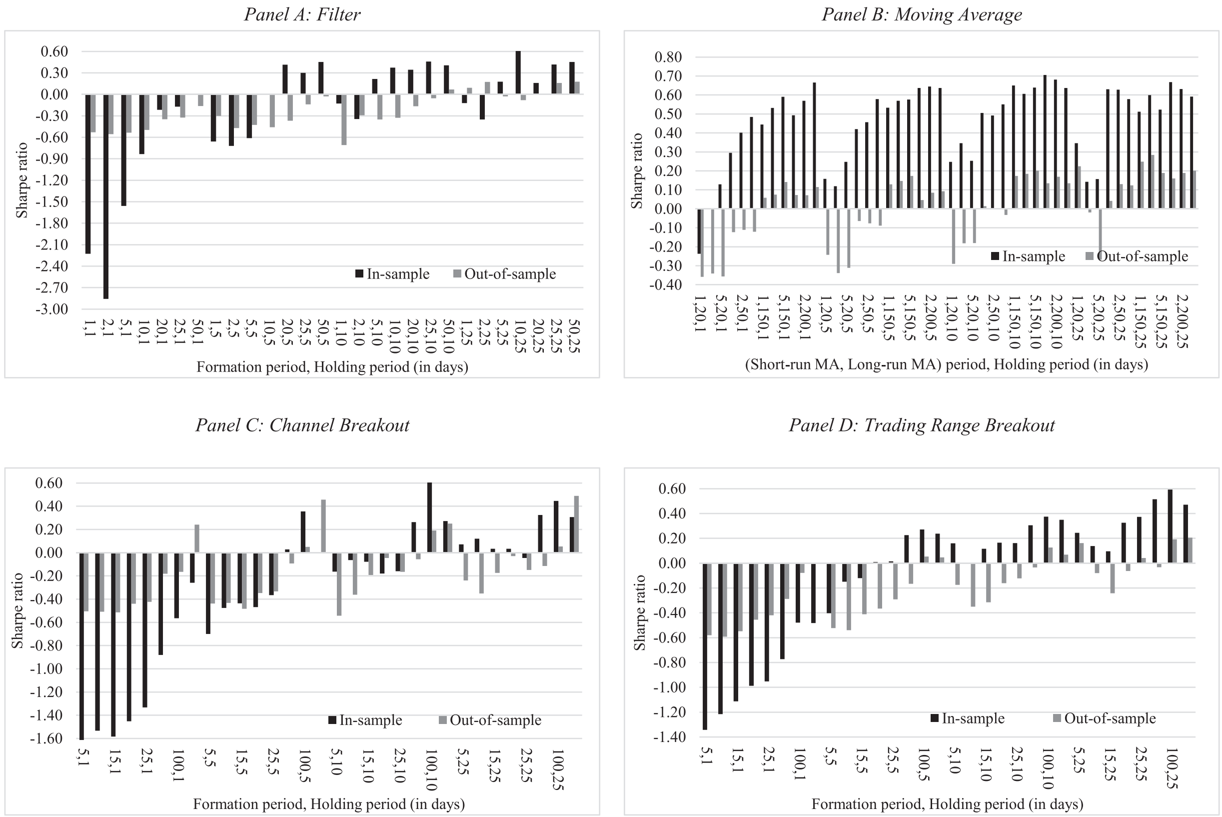

Fig. 1. Sharpe ratios for technical trading rule portfolio return series. Notes: The panels present the Sharpe ratios of the filter (A), moving average (B), channel breakout (C) and trading range breakout (D) technical trading rules. Sharpe ratios are calculated net of costs and for both in-sample and out-of-sample periods. The in-sample period is January 1980 to December 1998 and the out-of-sample period is January 1999 to April 2020. For filter rule (Panel A) portfolios are generated with the filter set at 1 % ($x = 1\%$). Moving average portfolios (Panel B) have a band of 0.5 % ($b = 0.5$ %). The channel breakout rule (Panel C) has a band of 1 % ($b = 1\%$) and the channel width of less than or equal to 10 % ($x = 10\%$). The trading range breakout rule portfolios (Panel D) are constructed with no bands ($b = 0$ %). In Panels A, C and D the x-axis shows the combination of formation period and holding period used to generate the portfolios. Here the portfolio (100,25) has a lookback period is 100 days and holding period 25 days. In Panel B, values on the x-axis report the number of days over which the short and long moving averages were calculated and the holding days. Here, (2200, 25) indicates a portfolio the short and long moving average were estimated over a 2-day period and a 200-day period, respectively, and a holding period of 25 days.

The is a noticeable difference in the out-of-sample analyses (Table 2, Panel C) where performance disappears across all trading strategies.

Accounting for transaction costs reduces profitability across all strategies, but in the full sample and in-sample periods (Panels A and B) most trading strategies survive transaction costs. The exception is CB, which has positive, but not statistically significant, returns in the full sample period. Out-of-sample, none of the strategies has a statistically significant return and FR has negative returns.

4.9. *Multiple strategy performance*

In this section, we consider performance across a range of parameterizations of the technical trading rules. The Sharpe ratios, net of transaction costs, for the in-sample and out-of-sample periods are displayed in Fig. 1 for the different technical trading strategies.

The pattern in the MA portfolios (Panel B) shows significant falls, typically from positive to negative across the different strategies. FR (Panel A), CB (Panel C) and TR (panel D) show generally consistent results, with decreasing performance out-of-sample. There are certain formations of FR and TR, at lower frequency, where performance improves out-of-sample, but remains negative. In general, Fig. 1 shows dissipating out-of-sample performance.

Next, we formally test the difference between out-of-sample and in-sample performance, using the three performance measures, average return, Sharpe ratio and risk adjusted return (Table 3). We first test if each measure is statistically different to zero and then if

Table 3
Out-of-sample versus in-sample performance This table presents results comparing out-of-sample and in-sample performance for all parametrisations of the technical trading rules. The cross sectional portfolio average return (Average Return), Sharpe ratios (Sharpe Ratio) and risk-adjusted alpha (Alpha) are reported for a combination of all trading rules (Panel A) and individually for each individual trading rule (Panels B-E). All performance values are presented gross of transaction costs. ***N*** is the number of observations; ***Mean*** is the annualised mean and ***Tstat*** is *t*-statistic of the corresponding mean value. *Out-of-sample - In-sample* is the difference between the in-sample and out of sample means and its significance is tested using the standard difference of means test, assuming the distributions have equal variance. The symbols ***, **, and * denote statistical significance at 1 %, 5 % and 10 % level of significance, respectively.

	Average Return			Sharpe Ratio			Alpha			N
	Mean		Tstat	Mean		Tstat	Mean		Tstat	
Panel A: All Strategies										
In-sample	3.29	***	(35.64)	0.62	***	(51.38)	3.91	***	(35.52)	388
Out-of-sample	0.28	***	(7.08)	0.06	***	(7.05)	0.40	***	(6.61)	388
Out-of-sample − In-sample	-2.92	***	(-29.88)	-0.56	***	(-37.44)	-3.39	***	(-27.88)	776
Panel B: Filter										
In-sample	3.54	***	(20.92)	0.61	***	(24.12)	4.48	***	(20.94)	84
Out-of-sample	0.34	***	(3.63)	0.05	***	(2.85)	-0.62	***	(-5.18)	84
Out-of-sample − In-sample	-3.10	***	(-16.50)	-0.56	***	(-17.86)	-4.90	***	(-20.76)	168
Panel C: Moving Average										
In-sample	4.74	***	(62.96)	0.72	***	(64.56)	5.51	***	(61.27)	144
Out-of-sample	0.56	***	(7.71)	0.09	***	(7.35)	1.13	***	(11.07)	144
Out-of-sample − In-sample	-4.00	***	(-39.44)	-0.63	***	(-39.29)	-4.17	***	(-31.74)	288
Panel D: Channel Breakout										
In-sample	0.65	***	(6.99)	0.38	***	(11.55)	0.72	***	(7.02)	64
Out-of-sample	-0.03		(-0.73)	0.09	***	(2.82)	0.05		(0.93)	64
Out-of-sample − In-sample	-0.68	***	(-6.66)	-0.29	***	(-6.46)	-0.67	***	(-5.93)	128
Panel E: Trading Range Breakout										
In-sample	2.68	***	(20.71)	0.63	***	(26.52)	3.18	***	(20.69)	96
Out-of-sample	0.02		(0.25)	0.02		(1.09)	0.43	***	(5.98)	96
Out-of-sample − In-sample	-2.60	***	(-18.62)	-0.62	***	(-21.73)	-2.67	***	(-16.18)	192

the difference between in-sample and out-of-sample means is significant.[4] We conduct these tests for all 388 parameterisations of the strategies, and then for all versions of the strategies in each class.

Panel A compares the full range of strategies. In-sample average returns are based on the distribution of average returns of all 388 portfolios constructed over the in-sample period. The test statistics suggest that in-sample, on average, portfolios generate statistically significant returns of 3.29 %. This falls to just 0.28 % in the out-of-sample period, although it remains statistically significant. Similarly, allowing for risk, the typical Sharpe ratio is 0.62 with an abnormal return of 3.91 % in the in-sample period. The value of these metrics, while still positive, declines significantly in the out-of-sample period (0.06 Sharpe ratio and 0.40 % alpha). The mean difference of the in-sample and out-of-sample distributions (out-of-sample minus in-sample) across the three metrics (average returns, Sharpe ratio and alphas) shows that the performance of trading strategies, overall, has dissipated. The results in Panels B-E are repeated for individual strategies, and show the same result, a statistically significant performance decline in the out-of-sample period.

Finally, we repeat the analysis net of transaction costs, limiting our sample to variations of strategies that yielded positive in-sample returns. Recall that, for the out-of-sample period, one-way transaction costs are six basis points from January 1999 to December 2002 and three basis points thereafter.

The results net of transaction costs, reported in Table 4, confirm the decline in profitability. The mean return and Sharpe Ratios of aggregate trading rules and all individual rule classes decline from statistically positive in-sample to negative or statistically zero out-of-sample. Only the Moving Average rule generates a statistically significant positive value for out-of-sample risk adjusted alpha but at a much lower level than in-sample. All remaining strategies and performance measures are either negative or zero out-of-sample.

5. Technical trading rules and momentum

In this section, we examine the relationship between technical trading rules and momentum. Both technical trading rules and momentum strategies rely on serial correlation in asset returns, so it seems reasonable to infer that they share a common source of returns. We specify principal component and regression analysis tests to demonstrate that the common factor underlying technical trading rules is time series momentum. To ensure our findings are generalizable, we also report results for a global currency sample.

5.1. Principal component and regression analyses

First, we construct time series momentum (TSM) portfolios following Moskowitz et al. (2012) where positions in currencies depend

[4] The statistical significance of the difference between in-sample and out-of-sample means is estimated using the standard difference of means test, assuming the distributions have equal variance.

Table 4
Out-of-sample versus in-sample performance net of transaction costs This table presents results comparing out-of-sample and in-sample performance for all parametrisations of the technical trading rules. The cross sectional portfolio average return (Average Return), Sharpe ratios (Sharpe Ratio) and risk-adjusted alpha (Alpha) are reported for a combination of all trading rules (Panel A) and individually for each individual trading rule (Panels B-E). All performance values are presented net of transaction costs. *N* is the number of observations; *Mean* is the annualised mean and *Tstat* is *t*-statistic of the corresponding mean value. *Out-of-sample - In-sample* is the difference between the in-sample and out of sample means and its *t*-statistic is based on a difference of means test assuming the distributions have equal variance. The symbols ***, **, and * denote statistical significance at 1%, 5 % and 10 % level of significance, respectively.

	Average Return			Sharpe Ratio			Alpha			N
	Mean		Tstat	Mean		Tstat	Mean		Tstat	
Panel A: All Strategies										
In-sample	2.15	***	(23.66)	0.35	***	(28.42)	2.78	***	(26.84)	255
Out-of-sample	-0.07		(-1.14)	-0.01		(-0.98)	0.08		(0.83)	255
Out-of-sample − In-sample	-2.18	***	(-19.96)	-0.37	***	(-21.25)	-2.63	***	(-19.28)	510
Panel B: Filter										
In-sample	1.73	***	(13.74)	0.28	***	(13.96)	2.72	***	(17.64)	41
Out-of-sample	-0.16		(-0.95)	-0.04		(-1.15)	-1.69	***	(-10.32)	41
Out-of-sample − In-sample	-1.86	***	(-8.96)	-0.32	***	(-8.65)	-4.31	***	(-19.55)	82
Panel C: Moving Average										
In-sample	3.03	***	(28.09)	0.45	***	(28.37)	3.76	***	(32.94)	138
Out-of-sample	0.06		(0.59)	0.00		(0.29)	0.63	***	(5.03)	138
Out-of-sample − In-sample	-2.89	***	(-20.48)	-0.45	***	(-20.04)	-3.03	***	(-18.28)	276
Panel D: Channel Breakout										
In-sample	0.25	***	(4.29)	0.18	***	(5.67)	0.29	***	(4.31)	24
Out-of-sample	-0.11		(-1.29)	0.04		(0.84)	-0.03		(-0.27)	24
Out-of-sample − In-sample	-0.36	***	(-3.51)	-0.15	***	(-2.56)	-0.31	***	(-2.61)	48
Panel E: Trading Range Breakout										
In-sample	1.03	***	(10.58)	0.23	***	(11.37)	1.39	***	(13.12)	52
Out-of-sample	-0.33	***	(-2.96)	-0.06	**	(-2.45)	0.07		(0.52)	52
Out-of-sample − In-sample	-1.35	***	(-9.18)	-0.29	***	(-9.22)	-1.30	***	(-7.85)	104

Table 5
Times series momentum relationship with technical trading rules Panel A presents the results of principal component analysis conducted on all specifications of (1) the time series momentum, (2) technical trading rules and (3) individual trading rule class portfolios. The table shows the cumulative percentage of variance explained by the first three common factors and pairwise correlation between factors. Panel B shows the results of regressing of the returns of (1) all technical trading rules and (2) individual trading rule classes on the returns of time series momentum. All returns are gross of transaction costs. *** denotes statistical significance at 1 % level of significance.

Panel A: Principal component analysis				
	% Variance explained	Time series momentum correlation		
		First	Second	Third
Time series momentum	77.47	1.00	1.00	1.00
Technical trading rules	75.97	0.96	0.43	0.56
Filter	74.82	0.06	0.14	0.23
Moving Average	88.97	0.61	0.64	0.67
Channel Breakout	76.11	0.06	0.12	0.08
Trading Range Breakout	80.98	0.44	0.59	0.66
Panel B: Regression analysis				
	α	β_{TSM}	R^2	
Technical trading rules	0.00	0.94***	0.88	
Filter	0.00	0.67***	0.31	
Moving Average	0.00	1.45***	0.90	
Channel Breakout	0.00	0.06***	0.22	
Trading Range Breakout	0.00	0.79***	0.71	

upon the past return of that currency. Kim et al. (2016) show that time series momentum returns are at least partially attributable to volatility scaling. We use equal weighting to ensure our results are not driven by volatility scaling. For TSM, each combination of formation and holding period (k, h) produces a distinct portfolio. For monthly trading $h,k \in \{1, 3, 6, 9, 12\}$, generating twenty-five TSM monthly portfolios (Moskowitz et al., 2012). We set $h, k \in \{1, 2, 3, 4, 6, 8, 12\}$ for weekly and $h, k \in \{1, 3, 5, 10, 15, 30, 60\}$ for daily trading, following Baltas and Kosowski (2013). This generates forty-nine further portfolios for TSM, at each frequency.

Panel A of Table 5 presents the results for principal component analysis carried out using gross portfolio return series of all TSM and technical trading rules over the full sample period (January 1980 to April 2020).[5] The cumulative percentage of variance explained by the first three principal components for individual trading class is as high as 78 %, on average. The pairwise correlation between the

[5] We use gross returns in this analysis to show that our results are not sensitive to the choice of transaction costs.

Table 6

Time series momentum states and technical trading rule performance The return series of the technical trading rules is partitioned into two subsamples, *TSM Positive* and *TSM Negative*, defined by the sign of the time series momentum portfolio in that month. The average return, Sharpe ratio and alpha in each of the subsamples is presented, along with the difference in means. The t-statistic (Tstat) is shown for each of the metrics. ***, **, * denote significance at the 1 %, 5 %, and 10 % levels, respectively.

	Average Return			Sharpe Ratio			Alpha			*N*
	Mean		Tstat	Mean		Tstat	Mean		Tstat	
TSM Positive	9.71	***	(11.41)	3.14	***	(11.41)	9.77	***	(6.37)	238
TSM Negative	-5.56	***	(-9.53)	-3.52	***	(-13.17)	-5.44	***	(-10.30)	246
Positive minus Negative	15.27	***	(14.83)	6.66	***	(17.36)	15.21	***	(9.13)	

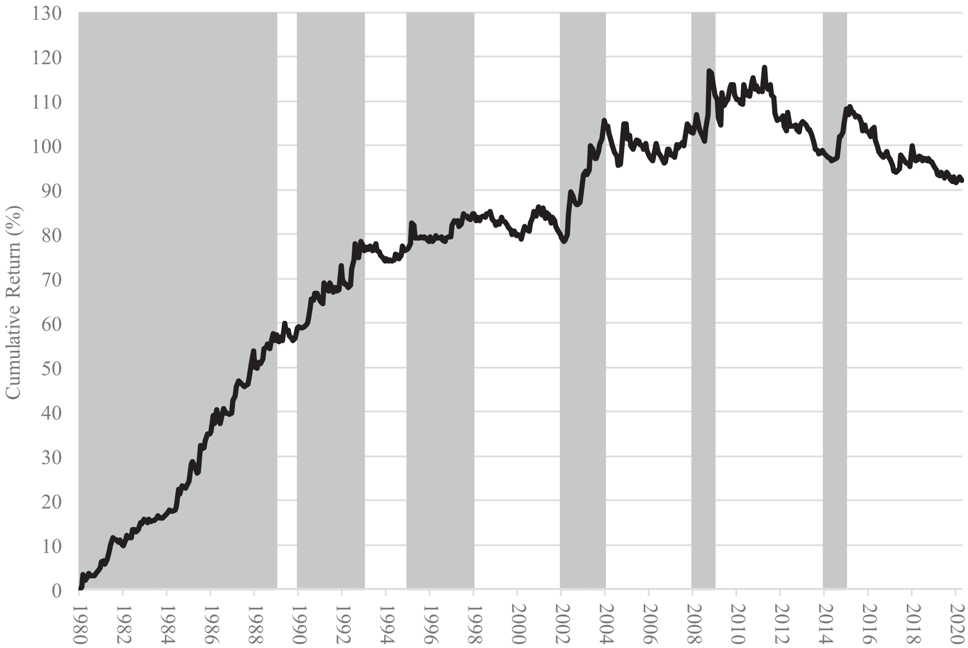

Fig. 2. Technical trading rule cumulative returns: Jan 1980 to April 2020. Depicted is the cumulative return of the equally weighted technical trading rule portfolio. Vertical grey bars indicate the twenty years out of forty-one in the sample in which the equal weighted time series momentum portfolio delivers an above-median return.

three TSM factors and the factors for the technical trading rules is also high. The first factors of TSM and the technical trading rules are almost identical with a correlation coefficient of 96 %. For both TSM and technical trading rules, the first factor explains over 50 % of the variance. While there is a decline in the correlation between second and third TSM factors, with the technical trading rule factors, these results indicate that technical trading rules share a common source of returns with TSM.

While PCA provides insights to common latent factors underlying the time series of variables, we adopt a widely used approach to test whether TSM accounts for the returns to technical trading rules, employing regression analysis to test the economic significance of alpha and the relationship between their returns.[6]

To do this we form equal weighted portfolios, rebalanced monthly, for time series momentum and technical trading rules using all available portfolios for each strategy. We then regress the returns of the technical trading portfolio on the returns of the time series momentum portfolio. In addition, we regress the returns of each individual class of trading rule on the TSM return series to get a more detailed view.

The results of the regression, presented in Table 5, Panel B, show an intercept that is not statistically different to zero, consistent with time series momentum fully explaining the returns to technical trading rules. In addition, the time series momentum beta is positive and highly statistically significant and the R^2 is 88 %, confirming the PCA finding of a close relationship between times series momentum and technical trading rules. A similar pattern is seen in the regressions for the individual technical trading rule classes, each has a sstatistically significant positive exposure to time series momentum and, after controlling for this exposure, none as an abnormal return different from zero.

[6] See for example, Moskowitz et al. (2012) and Goyal and Jegadeesh (2018).

Table 7

Times series momentum and technical trading rules for global currencies Panel A presents the results of principal component analysis conducted on all specifications of the time series momentum and technical trading rule portfolios. The table shows the cumulative percentage of variance explained by the first three common factors and pairwise correlations between factors. Panel B shows the results of regressing of the returns of the technical trading rules on the returns of time series momentum. All returns are gross of transaction costs. *** denotes statistical significance at 1 % level of significance. In Panel C the return series of the technical trading rules is partitioned into two subsamples, *TSM Positive* and *TSM Negative*, defined by the sign of the time series momentum portfolio in that month. The average return, Sharpe ratio and alpha in each of the subsamples is presented, along with the difference in means. The t-statistic (Tstat) is shown for each of the metrics. ***, **, * denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Panel A: Principal component analysis							
			% Variance explained	Time series momentum correlation			
				First	Second	Third	
Time series momentum			79.61	1.00	1.00	1.00	
Technical trading rule			79.17	0.83	0.38	0.52	
Panel B: Regression analysis							
			α	β_{TSM}	R^2		
Technical trading rule			0.00	0.66***	0.63		
Panel C: TSM and TTR performance in market states							
	Average Return		Sharpe Ratio		Alpha		*N*
	Mean	Tstat	Mean	Tstat	Mean	Tstat	
TSM Positive	3.37***	(9.44)	2.02***	(18.75)	3.27***	(8.72)	262
TSM Negative	-2.26***	(-6.35)	-1.82***	(-13.49)	-2.29***	(-6.15)	146
Positive minus Negative	5.63***	(11.17)	3.84***	(22.25)	5.56***	(10.52)	

To emphasize the reliance of technical trading rules on time series momentum we re-examine the performance of the equally weighted technical trading rule portfolio, but split the sample into two subsets following Bollen et al. (2021), depending on the sign of the return of the time series momentum portfolio return. The results, presented in Table 6, show that during positive momentum return months (approximately half of the sample period), the average performance of the technical trading rule portfolio is very high, with an average return of 9.7 % and a Sharpe ratio above 3. During negative momentum return months, in contrast, the results are reversed. The average return is − 5.6 %, with a Sharpe ratio of − 3.5. These results further highlight the importance of momentum in explaining the returns of technical trading rules.

Finally, we illustrate this relationship in Fig. 2, plotting the technical trading rule cumulative return along the x-axis. We highlight the twenty years in which time series momentum returns were above their median value with vertical grey bars. It is apparent that the technical trading rules generate much of their return during periods when momentum is successful. This is consistent with the idea that the technical trading rules share a common momentum-based return generating process.

5.2. Global currencies

The results above show that for G11 currencies the returns of technical trading rules can be fully explained by momentum. Hong and Stein (1999) show that momentum in stock markets is negatively correlated with information flow and market participant attention. In order to ensure our results are both generalizable to the broader currency market and robust to the specification of less liquid currencies, we repeat our empirical tests for a broader group of developed market currencies. If time series momentum explains technical trading rules, then the evidence should be consistent for other currencies.

To test the robustness of our main results to this view, we repeat the analyses from the preceding section for global currency portfolios formed using the same time series momentum and technical trading rules.

Results from PCA analysis, Table 7, Panel A, show that for global currencies the cumulative percentage of variance explained by the first three principal components is over 79 %, higher than the G11 currencies. Pairwise correlations between the three TSM factors and the factors for the technical trading rules also continue to be high, with the first principal component correlation being 0.83 (as compared to 0.96 for the G11 currency portfolios). Regression results, reported in Table 7, Panel B, confirm the PCA findings. Not surprisingly, given the wider cross sectional distribution of returns and volatility for the global currencies, the R^2 is 63 % (versus 88 % for the G11 currencies). Nonetheless, the relationship between momentum and technical trading rules is strong and the estimated alpha, which is the return from technical trading rules controlling for time series momentum, is zero.

Finally, we confirm that technical trading rule positive performance is concentrated in months when time series momentum returns are positive (Table 7, Panel B). Taken together these results confirm that technical trading rules share a common source of returns with momentum, even for a broader portfolio of global currencies.

6. Conclusions

In this paper we have replicated a comprehensive range of technical trading rules which have previously been shown to generate high returns in currency markets, focusing on the most liquid currencies, over an out-of-sample period up to April 2020.

We find diminishing evidence of performance out-of-sample. In-sample we find that each of the rules generate large and statistically significant risk-adjusted returns, in line with the existing literature. Out-of-sample the performance dissipates gross of transaction costs and disappears when transaction costs are applied. None of the four rules we analysed generates meaningful performance and none of their Sharpe ratios are statistically significant.

Most importantly, we document the strong link between technical trading rules and time series momentum. Using PCA, regression and portfolio analyses we show that time series momentum fully explains all of the returns to technical trading rules. When we decompose our sample period into months when time series momentum returns are positive and negative, we see that the returns to technical trading rules are generated in the periods when time series momentum generates positive returns.

The implications of our research for practitioner and academics are twofold. First our evidence shows that currencies have become more efficient over time with prices now incorporating technical trading rule information to such an extent that profit making opportunities at daily frequencies have dissipated. Second, our result show that in currency markets technical trading rule returns are, on average, indistinguishable from momentum.

In future work, it may be useful to investigate whether the strong relationship between technical trading rules and momentum, documented in this paper, extends to other asset classes. It would also be interesting to examine whether technical trading rules have a crash risk similar to momentum.

CRediT authorship contribution statement

Mark C. Hutchinson: Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Panagiotis E. Kyziropoulos:** Methodology, Software, Formal analysis. **John O'Brien:** Conceptualization, Methodology, Writing – review & editing. **Philip O'Reilly:** Supervision, Project administration, Funding acquisition. **Tripti Sharma:** Conceptualization, Methodology, Software, Formal analysis, Data curation. Writing – original draft.

Data availability

Data available online.

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